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Preface

Larger Danish transport projects are routinely subjected to cost-benefit analysis. For most infrastructure investments, the time savings evaluated by the value of travel time constitute the major part of user benefits. Thus, the value of travel time is often decisive for whether a project yields a positive or a negative economic benefit. It is therefore vital that the value is not only sound but also credible as its impact lies in the information that is given to policy makers concerning the projects analysed.

As a consequence, The Ministry of Transport and Energy has asked the Danish Transport Research Institute to carry out a study, leading to new values for travel time to be incorporated into the Ministry's guidelines for economic appraisal of transport projects.

Leading up to the present study was first a pre-study that lead to a phase 1 study in which a dataset was designed and collected. The present phase 2 study undertakes the econometric analysis of the data, leading to the value of travel time estimates to be used in future project evaluation.

The current note presents the methodology and the results of experiment 2: Disaggregated time components. Experiment 2 examines trading between hypothetical alternatives of the chosen mode and contains both in-vehicle and out-of-vehicle journey components (e.g. interchanges, access-egress, parking search). Detailed documentation is available in three other notes covering various parts of the study. A report also presents an overview of the methodology and summarises the main findings. These notes and report are available from DTF's home page.

Kgs. Lyngby, 2007

Niels Buus Kristensen
Director

Contents

1 Introduction

The primary purpose of the present note is to document the analysis of experiment 2 (SP2) in the Danish Value of Time Study: A within-mode abstract trading experiment using a sample of more than 4,000 respondents. The purpose of the analysis is to estimate the value of travel time (VTT) [1].

From experiment 1 (SP1) in the Danish Value of Time Study, we obtain values of free-flow driving time for car drivers and car passengers, and values of in-vehicle time (IVT) for public transport modes (see Fosgerau, Hjorth, Vincent Lyk-Jensen, 2007a).

SP2 examines a number of both in-vehicle and out-of-vehicle journey components. For car drivers/passengers the considered travel time components are free-flow driving time, congested driving time, access/egress walk time, and time spent searching for a parking space. For public transport users, travel time is decomposed into access/egress time, in-vehicle time (separate component for each transport mode), headway of the first used mode, number of interchanges between modes and associated waiting time.

Separate experiments are presented to car users, public transport users who use a single public transport mode for their journey, and public transport users who use multiple modes for their journey.[2]

For the last group of respondents, the experiment is divided into two parts; In the first part interchanges are held constant and in the second part one of the presented alternatives is reduced to use of a single mode.

All respondents that participated in the second experiment were presented with a total of eight choice situations based upon five different games.

The usual means of recommending values of out-of-vehicle time is to specify them relative to the value of in-vehicle-time (IVT). Indeed, recommending values of walking and waiting that are twice the value of IVT is a widespread convention.

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[1] We use this terminology, since the time changes we are evaluating may not be savings and since the value concerns travel time.

[2] Ferry users were not presented with the second experiment

The focus of the current analysis of SP2 is to obtain relative values of the considered travel time components. These relative values will be applied to the values of free-flow/in-vehicle time found in SP1. The combined results of the two experiments (SP1 and SP2) will then constitute a set of national values of travel time.

The methodology used for obtaining relative values of other travel time components from SP2 is described in section 2. Section 3 described experiment 2 and the data in details, while section 4 present the results and section 5 concludes the note.

2 Methodology

The time values are inferred from binary choices between alternative routes characterised by their cost and a vector of travel time components. All alternatives are obtained by varying some attributes of a real-life trip recently made by the respondent (reference trip). The purpose of this is to make the proposed alternatives seem realistic and familiar.

To estimate the values of different travel time components we model respondent's choice behaviour using a mixed logit model. The model description in this section reflects the step-by-step procedure of the modelling: We begin with a simple base model, which is then extended to take account of certain characteristics of the experimental design and to allow for reference-dependent preferences.

We assume that the values of the time components are positive, depend on observed characteristics of the respondent and the trip, and are random over the population to allow for unobserved heterogeneity. We do not attempt to estimate a separate distribution for each time component. Instead we aim at estimating the relative values of the components, assuming that all components share the same distribution, except for a scale factor.

We analyse each mode or mode combination separately. Hence we have 8 different data segments:

- Car,
- Single-mode public transport (PT):
  - bus,
  - metro,
  - S-train,
  - train,
- Multiple-mode public transport (PT):
  - bus-metro,

- bus-train (here S-train is included in the train mode),
- metro-train (here S-train is included in the train mode).

Section 2.1 describes our base model. In sections 2.2-2.4 we enhance this model by allowing for reference-dependent preferences and distance-specific time values, and discuss how to model the headway variable (only public transport modes).

2.1 Base model

2.1.1 Notation

c_1, c_2: the costs of alternative 1 and 2

t_1, t_2 : vectors of time components of alternative 1 and 2.

x: vector of covariates

For car drivers/passengers, each t_j consists of the following components:

$$t_j = (t_j^{ff}, t_j^{cng}, t_j^{eg}, t_j^{pk}),$$

where

t_j^{ff}: free-flow driving time for alternative *j*, in minutes.

t_j^{cng}: congested driving time for alternative *j*, in minutes.

t_j^{eg}: egress walk time (time spent walking to/from the car) for alternative *j*, in minutes.

t_j^{pk}: parking time (time spent searching for a parking space) for alternative *j*, in minutes.

For public transport users using a single transport mode,

$$t_j = (t_j^{iv}, t_j^{ae}, t_j^{hdw}, t_j^{ch}, t_j^{wt})$$

where

t_j^{iv}: total in-vehicle time for alternative *j*, in minutes.

t_j^{ae}: access/egress time (time spent travelling from the origin to the public transport mode and from the public transport mode to the destination) for alternative *j*, in minutes.

t_j^{hdw}: headway (time between departures of first public transport mode) for alternative *j*, in minutes.

t_j^{ch}: number of interchanges (between two vehicles of the same type, e.g. two busses) for alternative *j*.

t_j^{wt}: total waiting time associated with interchanges for alternative *j*, in minutes.

For public transport users where at least one of the alternatives uses multiple modes,

$$t_j = (t_j^{ivMODE1}, t_j^{ivMODE2}, t_j^{ae}, t_j^{hdw}, t_j^{ch}, t_j^{wt})$$

where

$t_j^{ivMODE1}$: in-vehicle time in mode 1 for alternative *j*, in minutes.

$t_j^{ivMODE2}$: in-vehicle time in mode 2 for alternative *j*, in minutes.

t_j^{ae}: access/egress time (time spent travelling from the origin to the first public transport mode and from the last public transport mode to the destination) for alternative *j*, in minutes.

t_j^{hdw}: headway (departure frequency of first public transport mode) for alternative *j*, in minutes.

t_j^{ch}: number of interchanges (between two vehicles of different type) for alternative *j* (equals 0 for single-mode alternatives and 1 for multiple-mode alternatives).

t_j^{wt}: total waiting time associated with interchanges for alternative *j*, in minutes.

Note that, for public transport users, walking time associated with interchanges is not explicitly included as a component of travel time. When presenting alternatives to the respondents, interchanges and interchange waiting time are described to respondents in the following way: "The journey involves no interchanges", or "The journey involves two interchanges with a total interchange waiting time of 10 minutes". Walking time is not mentioned, which means that we cannot know if respondents interpret it as included in the interchange waiting time, or as a fixed penalty associated with an interchange.

2.1.2 Values of time components

Consider an individual *n* in choice situation *r*. Let x_{nr} denote the associated covariate vector (which contains individual-specific and trip-related variables), and let VTT_{nr} denote his vector of time values. We assume that

$$VTT_{nr} = \exp(\beta' x_{nr} + u_n)(1, \exp(\alpha_2), \exp(\alpha_3), ..., \exp(\alpha_K)) \quad (1)$$

where *K* is the number of time components, β and $\alpha_1,...,\alpha_K$ are parameters, and u_n is a person-specific random variable independent of x_{nr}. The u_n's are independent across individuals, and represent unobserved heterogeneity (taste variation).

From the analysis of experiment 1 in the Danish Value of Time Study, we know that the value of in-vehicle time can be assumed to be lognormal for most public transport modes, and we therefore assume that the u_n's follow a $N(\bar{u}, \sigma^2)$ distribution, which is equivalent to the VTT having a lognormal distribution. As in the analysis of experiment 1, the assumption of lognormal time values will be tested by estimating models where the distribution of the u_n's is a flexible transformation of the normal distribution (following the methodology in Fosgerau and Bierlaire, 2005). However, since it is not the mean value of travel time, we are interested in, but the relative values of time components, the choice of distribution only matters if it affects the relation between different components.

We make the following observations regarding eq. (1)

- The value of the first time component is estimated directly as $E(\exp(\beta' x_{nr} + u_n))$. The value of the *i*'th time component (*i* ≥ 2) is $\exp(\alpha_i)$ times the value of the first component. Thus, all time values are positive and depend in the same way on observable and unobservable characteristics of the respondents.

- The α_i's are constant across the population. Hence the relative time values are the same for all individuals.

- The time value components are perfectly correlated lognormal random variables with mean $\exp(\beta' x_{nr} + \alpha_i + \bar{u} + \sigma^2/2)$ and variance $\exp(2(\beta' x_{nr} + \alpha_i))(\exp(\sigma^2) - 1)\exp(2\bar{u} + \sigma^2)$.

Since the objective of the analysis is to obtain relative time values compared to free-flow driving time or in-vehicle time, we choose this as the first time component[3]. Hence, we model all time values in terms of the value of free-flow time or in-vehicle time.

In the SP1 analysis the focus was on explaining the random and systematic variation in the values of free-flow time and in-vehicle time. In the current analysis we are not interested in these time components, and we therefore do not include covariates. Hence in the following models, we drop the term $\beta' x_{nr}$ from eq. (1).

2.1.3 Modelling choices

We characterise alternatives in terms of their generalised cost (GC), which we define as the travel cost plus the monetary equivalent of the time components. For respondent *n* in choice situation *r*, the generalised cost of alternative *j* is

$$GC_{nrj} = c_{nrj} + \exp(u_n)(1, \exp(\alpha_2), \exp(\alpha_3), ..., \exp(\alpha_K))\, t_{nrj} \quad (2)$$

Note that the generalised cost is linear in the travel time attributes. For some attributes, this is an acceptable assumption, while for others it will be relaxed at a later stage.

We assume that respondents choose the alternative with the lowest generalised cost, however we allow for them to make errors and assume that these errors are independent across choices.

Denoting the alternatives 1 and 2, and letting Y_{nr} denote the discrete choice variable, our base model can be written

$$Y_{nr} = 1 \quad \Leftrightarrow \quad -\log[GC_{nr1}] + \frac{\varepsilon_{nr1}}{\mu} \geq -\log[GC_{nr2}] + \frac{\varepsilon_{nr2}}{\mu} \quad (3)$$

[3] For the multiple-mode games, we choose one of the two in-vehicle times. See section 2.5.

where μ is a scale parameter, and the ε_{nrj}'s are mutually independent and identically distributed choice-specific random variables following a standard Gumbel distribution. We further assume the ε_{nrj}'s to be independent of the generalised costs.

Because the model is formulated in terms of the log of the generalised cost, the errors are multiplicative to the generalised cost. This means that large absolute errors are more likely to occur in choices with higher generalised costs. This is not just an arbitrary assumption: In our initial analysis we have made various comparisons of models with multiplicative errors and models with additive errors (which are commonly used in discrete choice models). We find that models with multiplicative errors fit the data much better – they convincingly outperform models with additive errors. Documentation of these comparisons is given in the Appendix.

Since $\frac{1}{\mu}(\varepsilon_1 - \varepsilon_2)$ follows a logistic distribution with scale μ and location zero, the probability that individual *n* chooses alternative 1 in choice situation *r,* conditional on his unobserved characteristics, is

$$P(Y_{nr} = 1 | u_n) \quad = \quad \frac{1}{1 + \exp[-\frac{1}{\mu}(\log(GC_{nr2}) - \log(GC_{nr1})]} \tag{4}$$

Since we assume that people always choose one of the two alternatives, the probability of choosing alternative 2 is (1 - $P(Y_{nr} = 1 | u_n)$). Using that the error terms are independent across choices, we find that the conditional probability of making a series of choices ($y_{n1}, \ldots, y_{nR}$) is

$$P(y_{n1},\ldots,y_{nR} | u_n) \quad = \quad \prod_{r=1}^{R} P(Y_{nr} = y_{nr} | u_n) \tag{5}$$

Letting f denote the density of u, we can write the likelihood contribution from individual *n* as

$$P(y_{n1},\ldots,y_{nR}) \quad = \quad \int \prod_{r=1}^{R} P(y_{n1},\ldots,y_{nR} | u_n) f(u)\, du \tag{6}$$

In the remainder of the section, we suppress the subscript *r* in the model formulations.

2.2 Headway formulation

In our base model, we assume that the generalised cost of an alternative is linear in the time attributes, and hence each time component has a constant unit value for each individual. For attributes as in-vehicle time or access/egress time, this is an acceptable assumption, as the attribute levels are amounts of time the respondent must spend on the corresponding activities.

However, we cannot assume that the value of headway is linear in the attribute. We consider it likely that a change in frequency from one departure every 5 minutes to one departure every 10 minutes may have a relatively large cost: Respondents do not bother to plan their arrival at the station when departure frequency is so high, which means that the extra time between departures would cause people to wait longer at the station. However, we do not expect a change in frequency from 30 minutes to 35 minutes to have a similar effect: For such high headway levels, respondents do bother to plan their arrival at the station, meaning that a change from 30 to 35 minutes will not cause much extra waiting time at the station, but instead a reduced ability to plan flexibly, and perhaps extra waiting time at the origin or destination of the journey.

Since there are only eight levels of the headway variable, it is possible to model separate values for different levels. The generalised cost can still be represented by eq. (2), only with the vector of time components including a set of dummy variables instead of t_j^{hdw}. For the single-mode public transport experiment[4], the generalised cost becomes

$$\begin{aligned} GC_{nj} = \quad & c_{nj} + \exp(u_n)[t_{nj}^{iv} + \exp(\alpha_{ae})t_{nj}^{ae} \\ & + \exp(\alpha_{ch})t_{nj}^{ch} + \exp(\alpha_{wt})t_{nj}^{wt} \\ & + \exp(\alpha_{hdw5})1\{t_{nj}^{hdw} = 5\} + \exp(\alpha_{hdw10})1\{t_{nj}^{hdw} = 10\} \\ & + \exp(\alpha_{hdw15})1\{t_{nj}^{hdw} = 15\} + \exp(\alpha_{hdw20})1\{t_{nj}^{hdw} = 20\} \\ & + \exp(\alpha_{hdw30})1\{t_{nj}^{hdw} = 30\} + \exp(\alpha_{hdw60})1\{t_{nj}^{hdw} = 60\} \\ & + \exp(\alpha_{hdw120})1\{t_{nj}^{hdw} = 120\}] \end{aligned} \qquad (7)$$

The base is “less than 5 minutes”.

[4] The expression for the multiple-mode experiment is similar, only with two in-vehicle times.

Based on the estimated headway parameters $\alpha_{hdw5} \dots \alpha_{hdw120}$, we can check whether people value headway the way we expect them to – i.e. that the difference in generalised cost between two large headway values is relatively small or perhaps zero. We compare the model defined by eq. (7) to a model where the generalised cost increases linearly with the time between departures, but with different slopes below and above a certain level of headway H^*. For the single-mode experiment, this will be

$$\begin{aligned} GC_{nj} = \quad & c_{nj} + \exp(u_n)[t_{nj}^{iv} + \exp(\alpha_{ae})t_{nj}^{ae} \\ & + \exp(\alpha_{ch})t_{nj}^{ch} + \exp(\alpha_{wt})t_{nj}^{wt} + \exp(\alpha_{hdwLOW})1\{t_{nj}^{hdw} \le H^*\} \\ & + \exp(\alpha_{hdwHIGH})1\{t_{nj}^{hdw} > H^*\}] \end{aligned} \quad (8)$$

As mentioned in the beginning of the section, attribute values are obtained by varying the attribute level of a reference trip. When asked about the reference trip, a small number of respondents have stated that they do not know the headway of their first used mode. Since there is no reference level for the presented headway attributes to vary around, these respondents are presented with headway values of 60 and 120 minutes.

However, headway levels of 60 and 120 minutes may seem unrealistic for some of these respondents, especially regarding high-frequency transport modes as city busses, metro, and S-train. We cannot predict how this would affect their choices, but we attempt to control for potential deviations by allowing respondents with missing headway reference to value headway differently. We do this by including in the generalised cost two dummies for missing headway reference – one for t_j^{hdw} = 60 and one for t_j^{hdw} = 120. The model with headway dummies thus becomes

$$\begin{aligned} GC_{nj} = \quad & c_{nj} + \exp(u_n)\left[\; t_{nj}^{iv} + \exp(\alpha_{ae})t_{nj}^{ae} \right. \\ & + \exp(\alpha_{ch})t_{nj}^{ch} + \exp(\alpha_{wt})t_{nj}^{wt} \\ & + \exp(\alpha_{hdw5})1\{t_{nj}^{hdw} = 5\} + \exp(\alpha_{hdw10})1\{t_{nj}^{hdw} = 10\} \\ & + \exp(\alpha_{hdw15})1\{t_{nj}^{hdw} = 15\} + \exp(\alpha_{hdw20})1\{t_{nj}^{hdw} = 20\} \\ & + \exp(\alpha_{hdw30})1\{t_{nj}^{hdw} = 30\} + \exp(\alpha_{hdw60})1\{t_{nj}^{hdw} = 60\} \\ & + \exp(\alpha_{hdw120})1\{t_{nj}^{hdw} = 120\} \\ & \left. + 1\{\text{Miss\_hdw} = 1\}\left(\beta_{hdw60m}1\{t_{nj}^{hdw} = 60\} + \beta_{hdw120m}1\{t_{nj}^{hdw} = 120\}\right) \;\right] \end{aligned} \quad (9)$$

And the model with piecewise linear headway becomes

$$
\begin{aligned}
GC_{nj} = \quad & c_{nj} + \exp(u_n)\,\Big[\; t_{nj}^{iv} + \exp(\alpha_{ae}) t_{nj}^{ae} \\
& + \exp(\alpha_{ch}) t_{nj}^{ch} + \exp(\alpha_{wt}) t_{nj}^{wt} \\
& + \exp(\alpha_{hdwLOW}) 1\{t_{nj}^{hdw} \le H^*\} \\
& + \exp(\alpha_{hdwHIGH}) 1\{t_{nj}^{hdw} > H^*\} \\
& + 1\{\text{Miss\_hdw} = 1\}\big(\beta_{hdw60m} 1\{t_{nj}^{hdw} = 60\} + \beta_{hdw120m} 1\{t_{nj}^{hdw} = 120\}\big)\;\Big]
\end{aligned} \tag{10}
$$

For the metro segment, there are very few high headway values. Of the 1,686 headway attributes (in 843 choices) only 49 are 20 or 30 minutes, and 49 are 60 or 120 minutes. With the exception of a single choice, headway values are only 60 or 120 when headway reference is missing. We therefore need to simplify the headway formulation in the metro models:

1. In the model with headway dummies we can only estimate one dummy for headway level 60 and one for level 120 – we cannot control for missing headway reference. Also we have to use a single dummy for headway levels 20 and 30.

2. In the model with piece-wise linear headway, we combine the two missing headway dummies in a single dummy. Still, it may not be possible to estimate two different slopes for low and high headway values together with a dummy for missing headway reference. The reason is that most of the observations with high headway values also have missing headway reference. If this is the case, we shall instead try a model where headway is linear (as in the base model), but include the missing headway dummy to allow for different valuations for higher headway levels.

2.3 Reference-dependent preferences

As in the analysis of SP1, we incorporate reference-dependent preferences in our model. The application of reference-dependence is based on prospect theory (see Kahneman and Tversky 1979, and Tversky and Kahneman, 1991), according to which people make choices based on the perceived values of the time and cost attributes, rather than the actual values of the attributes. The perceived value depends on a reference, which may be the current situation, and on whether the attribute represents a loss or a gain relative to the reference. Thus prospect theory allows for loss aversion (that the impact of a change is greater if the change is a loss than if it is a gain), which can explain the willingness-to-pay/willingness-to-accept gap often found in valuation experiments[5]. We use the formulation of de Borger and Fosgerau (2006) to infer a value of time that is “reference-free”, i.e. we control for the effect of loss aversion.

In the current experiment, all alternatives are obtained by varying some attributes of a recent trip made by the respondent. Respondents are instructed to imagine that they are to repeat the trip, only with different travel times and costs. With this focus, we expect that the real-life trip becomes a base of comparison, such that a lower cost than the real is perceived as a gain, while a higher is perceived as a loss. Accordingly, the reference is defined as the real-life trip.

Consider an attribute of an alternative, e.g. the travel cost c_j. We assume that respondents perceive c_j as the reference cost c_0 (the cost of the real trip) plus a change $\Delta c = c_j - c_0$. If $c_j > c_0$, the change is perceived as a loss, otherwise as a gain. Hence the perceived value of c_j is

$$val(c_j \mid c_0) \quad = \quad c_0 + (c_j - c_0) \cdot e^{\eta_c S(c_j - c_0)} \tag{11}$$

where $S(\Delta c)$ denotes the sign of Δc, and η_c is a parameter. Note that people exhibit loss aversion with respect to travel cost if $\eta_c > 0$.

To allow for loss aversion in our model, we simply replace the vector of time components in eq. (2) by a vector of perceived values of the time components, all having the form given by eq. (11). However, we must take into account that:

- Respondents may not have a reference. As mentioned, this is sometimes the case for the headway variable, as a few respondents do not know the headway of the real trip. For these respondents, we set the perceived value of the headway attribute equal to the actual attribute value.

- There may not be enough variability around the reference to identify η. For some time components, such as parking time or the number of interchanges, almost all attribute values are larger than the reference value. In this case it is not possible to identify η, and hence we just use the actual attribute values without controlling for reference-dependence. Section 3 identifies the relevant time components.

---

[5] See e.g. Kahneman and Tversky (1979) or the review by Horowitz and McConnell (2002).

2.4 Distance-specific parameters

To examine whether the values of the travel time components depend on the length of the trip, we estimate a model with separate time values for short and long trips. The generalised cost is

$$\begin{aligned} GC_{nj} = \quad & val(c_{nj} \mid c_{n0}) \\ & + 1\{dist_n \le D\} \cdot e(u_n^S)(1, \exp(\alpha_2^S), \exp(\alpha_3^S), ..., \exp(\alpha_K^S))t_{nj} \\ & + 1\{dist_n > D\} \cdot e(u_n^L)(1, \exp(\alpha_2^L), \exp(\alpha_3^L), ..., \exp(\alpha_K^L))t_{nj} \end{aligned} \quad (12)$$

where *dist* is the length of the reference trip (distance travelled), and *D* is the maximum distance for short trips. t_{nj} is a vector of time components or their value functions.

The choice of *D* is of course specific to the transport mode. We define short trips as trips shorter than the median trip length (rounded to the nearest 5 km).

We do not estimate distance-specific parameters for the metro segment for two reasons:

- It is a rather small segment.
- The reference trips are generally very short – the mean distance travelled is around 7.5 km.

Segment	***D***
Car	25 km
PT single-mode Bus	10 km
PT single-mode S-train	15 km
PT single-mode Train	50 km

The multiple-mode samples are too small to estimate distance-specific parameters (see section 3).

2.5 Multiple-mode PT game

The multiple-mode public transport experiment deserves extra attention, as it consists of three small experiments (A, B, and C) with slightly different designs. Choices involve two modes (mode 1 and mode 2), combined in three different ways:

A. Four choices where all alternatives use both mode 1 and mode 2. The number of interchanges is always 1.

B. Two choices where one alternative uses mode 1 and the other both mode 1 and mode 2.

C. Two choices where one alternative uses mode 2 and the other both mode 1 and mode 2.

In this design, mode 1 is the first mode used on the reference trip, and mode 2 is the second. In the multiple-mode alternatives this sequence is maintained. From the experiment, we are able to distinguish in-vehicle time by transport mode (bus, metro, train) and by

- whether both alternatives use both modes, or one alternative uses only a single mode
- whether the mode is used alone or in combination with another mode
- whether the mode used in the single-mode alternative is the first or the second used on the reference trip (mode order)

The first distinction is observed by comparing part A to parts B and C. The second is observed by comparing single-mode alternatives to multiple-mode alternatives, within part B and part C. The third is observed by comparing part B to part C.

We first discuss the first distinction: In part A, choices are between two multiple-mode alternatives, and the number of interchanges is fixed to one for all alternatives. In parts B and C, each choice is between a single-mode alternative and a multiple-mode alternative. Even though the respondents are the same in the three parts, it is possible that some parameters differ between part A and parts B and C:

- Valuation in part A may differ from valuation in parts B and C. Alternatives are more similar in part A, and this may shift attention from some time components to others.
- The error scale (μ) might differ between part A and parts B and C. The fact that alternatives are more similar in part A could ease comparison and cause smaller errors in part A. Also, the number of attributes in part A differs from that in parts B and C, as interchanges are kept constant. This may affect the processing of information.

Based on this, we want to allow parameters to differ between part A and parts B and C.

As for the other two distinctions listed on the previous page we make some simplifying assumptions: First, we assume that the mode order does not affect the time values. This is because the in-vehicle time of interest is the time spent in a given transport mode, regardless of the order. The assumption implies that part B in the (bus, metro) segment is equivalent to part C in the (metro, bus) segment, and vice versa. We can therefore combine the two segments (and similarly for bus-train and metro-train combinations).

Further, we assume that within parts B and C, the value of in-vehicle time depends only on transport mode, and not on whether alternatives use a single mode or multiple modes. This assumption is based on results from the initial modelling process[6].

In summary, our modelling strategy for the multiple-mode experiment is as follows: We want to estimate parts A, B and C jointly, but allow for different time values and scales – one set of values in part A and another in parts B and C.

The base model for the multiple-mode experiment is similar to the base model in section 2.1, except that the generalised cost and the scale of the error terms differ between part A and parts B and C. In part A the generalised cost is given by

$$\begin{aligned} GC_{nj}^{A} = c_{nj} + \exp(\bar{u}^{A} + v_n)\big[\ & t_{nj}^{ivMODE1} + \exp(\alpha_{ivMODE2}^{A}) t_{nj}^{ivMODE2} \\ & + \exp(\alpha_{ae}^{A}) t_{nj}^{ae} + \exp(\alpha_{ch}) t_{nj}^{ch} + \exp(\alpha_{wt}^{A}) t_{nj}^{wt} + \exp(\alpha_{hdw}^{A}) t_{nj}^{hdw}\ \big] \end{aligned} \tag{13}$$

And in parts B and C it is

$$\begin{aligned} GC_{nj}^{BC} = c_{nj} + \exp(\bar{u}^{BC} + v_n)\big[\ & t_{nj}^{ivMODE1} + \exp(\alpha_{ivMODE2}^{BC}) t_{nj}^{ivMODE2} \\ & + \exp(\alpha_{ae}^{BC}) t_{nj}^{ae} + \exp(\alpha_{ch}) t_{nj}^{ch} + \exp(\alpha_{wt}^{BC}) t_{nj}^{wt} + \exp(\alpha_{hdw}^{BC}) t_{nj}^{hdw}\ \big] \end{aligned} \tag{14}$$

In this formulation, mode 1 denotes the base time component, of which all other components are multiples. This is bus in-vehicle time for the bus-metro and bus-train segments, and metro in-vehicle time for the metro-train segment. The v_n's are independent $N(0,\sigma^2)$ person-specific random

[6] These results are not included here, but are available on request.

variables, and $\bar{u}^A, \bar{u}^{BC}$ are constants[7]. Since the number of interchanges is always one in part A, we cannot estimate a part-specific value of an interchange, hence the common parameter for all parts.

By imposing restrictions on the base model, we test whether the α's can be assumed to be the same in part A and parts B and C.

[7] We use this notation because the constants correspond to the mean ($\bar{u}$) of the random variable u_n in eqs. (1) and (2). In eqs. (13) and (14) we "decompose" the taste heterogeneity parameter u_n into a constant and a random variable with zero mean. This allows us to use the same draw v_n in both equations, corresponding to unobserved factors affecting time values in the same direction in the three parts.

3 Data

In the survey, respondents were first asked to describe a recently undertaken trip (the reference trip) by a specific transport mode. Business trips were not included. Afterwards they participated in up to four experiments.

All respondents took part in the first experiment (SP1), which consisted of binary choices between travel alternatives characterised by the cost and travel time. Most respondents also participated in the second experiment (SP2), which was similar to SP1, except that several components of travel time were allowed to vary. The remaining two experiments were a repetition of SP1 only with an alternative mode (SP3), and a contingent valuation experiment where travel time and money were traded directly (SP4).

Depending on their reference trip, respondents took part in one of three SP2 games: A car game, a single-mode public transport game, and a multiple-mode public transport game. The data structure of SP2 is summarized in the table below. Each of the three games consists of eight choices.

The presented alternatives were described by absolute journey time, cost values and number of interchanges and not as changes to the observed journey time, cost and interchanges.

Table 1: Data description

Transport mode	Time components	No. of choices per individual
Car	Car components	8
Single–mode PT	PT single-mode components	8
Multiple-mode PT	PT multiple-mode, part A, components - Interchanges constant	4
	PT multiple-mode, part B, components – One alternative reduced to use of single mode (PT mode 1)	2
	PT multiple-mode, part C, components – One alternative reduced to use of single mode (PT mode 2)	2

3.1 Car game

The respondents participating in the car game are car respondents from SP1 that are likely to experience at least one of the following components: congestion, parking search time, and egress walk time. For a given respondent, only the components that are considered to be familiar to the respondent are included in the experiment.

The game consists of eight binary choices. In general, alternatives are characterised by

- cost,
- free-flow driving time,
- congested driving time,
- parking search time,
- egress walk time.

If any of the latter three components is not familiar to the respondent, the variable is dropped. All alternatives have the same transport mode as on the reference trip (car driver or passenger).

3.2 Single-mode public transport game

Respondents who used a single public transport mode (bus, metro, S-train, or train) on the reference trip participated in the single-mode experiment. Again, the experiment consisted of eight binary choices. All alternatives used a single transport mode, which was the mode from SP1, namely the main mode of the reference trip.

Alternatives are characterised by

- cost,
- headway,
- access/egress time,
- in-vehicle time,
- number of interchanges and interchange waiting time

Note that interchanges in this experiment are interchanges between two vehicles of the same type, e.g. two busses.

3.3 Multiple-mode public transport game

Respondents participate in this experiment only if they use one of the following mode combinations on the reference trip: bus-metro, bus-train, or metro-train.[8] Again respondents are faced with eight binary choices. Choices involve two modes (mode 1 and mode 2), that constitute one of the above combinations. Note that the main mode on the reference trip (the mode used in SP1) is always one of the two.

The attributes characterising the alternatives are the same as in the single-mode experiment, except that a separate in-vehicle time is stated for each used mode. There are no interchanges between vehicles of the same type, hence the number of interchanges is always zero for the alternatives using a single transport mode, and one for alternatives using two modes.

3.4 Samples

We use only observations from respondents used in the analysis of SP1. This means that data is already "cleaned" with respect to factors as

- unrealistic travel times, costs,
- too high share of congestion (maximum is 70%)
- too large travel group size for car modes
- too small main mode travel time share for public transport
- too high waiting, access, or egress times for public transport.

Hence for SP2 we need only investigate variables specific to the second experiment and related background variables.

3.4.1 Data exclusion

We observed that the dataset encompass some dominant choices, i.e. choices for which one alternative was both cheaper and fastest for all the time components, see the Appendix for further details.

[8] Notice that S-train is included in the train mode.

In the car experiment, 32% of all choices were dominant choices.[9] These have been excluded from the current analysis, as well as all observations regarding respondents who chose a dominated alternative. (The table below gives an overview of the number of respondents who failed the dominant choice and will be excluded).

Experiment		**# respondents choosing the dominated alternative**	**# respondents (before exclusions)**
Car		135	1579
PT – Single mode		55	2073
PT – Multiple mode	Part A	7	818
	Part B	0	818
	Part C	0	818

For the car users sample we have further excluded unrealistic parking search time (=310 minutes, 1 respondent), egress walk time (>60 minutes, 0.8% of the respondents) and one observation for a respondent living in a town with less than 5,000 inhabitants, who has experienced no congestion in his reference trip and who should not have been asked on congestion. His journey was 75 minutes and he was suggested a congested time of 73 minutes.

For both single- and multiple-mode PT, if the headways variable was missing in one of the suggested alternatives (had a value of zero), the choices have been excluded (387 observations in single-mode PT, 2 % and 62 for multiple-mode PT part A, 2 %). Access or egress times larger than 60 minutes were excluded (0.7 % of the respondents in the single-mode experiment, 1% in the multiple-mode experiment)

For multiple-mode PT, all in-vehicle times in Part A had to be positive as both alternatives use mode 1 and mode 2. However, in Part A there are 20 observations where at least one in-vehicle time is zero. In Parts B and C, at the most one of the in-vehicle times in a given choice should be zero, namely for the unused mode in the single-mode alternative. In each of Part B and C, there are 10 observations for which more than one in-vehicle time is zero. These observations are excluded.

The following tables show the sample sizes after exclusions.

[9] This high proportion is due to an SP design error.

Table 2: Sample sizes

Experiment		# respondents	# choices
Car		1437	7888
PT – Single mode		1996	13474
PT – Multiple mode	Part A	789	2885
	Part B	790	1579
	Part C	789	1570

Table 3: Modal distribution, car experiment

	# respondents	# choices
Car drivers	1185	6523
Car passengers	252	1365

Table 4: Modal distribution, PT single-mode experiment

	# respondents	# choices
Bus	1103	7472
Metro	126	843
S-train	264	1822
Train	503	3337

Table 5: Modal distribution, PT multiple-mode experiment

Mode 1	Mode 2		# respondents	# choices
Bus	Metro	Part A	67	252
		Part B	67	134
		Part C	67	133
		All	67	519
Metro	Bus	Part A	37	130
		Part B	37	74
		Part C	37	74
		All	37	278
Bus	Train	Part A	268	977
		Part B	268	536
		Part C	267	528
		All	268	2041
Train	Bus	Part A	268	984
		Part B	269	537
		Part C	269	538
		All	269	2059
Metro	Train	Part A	49	172
		Part B	49	98
		Part C	49	97
		All	49	367
Train	Metro	Part A	100	370
		Part B	100	200
		Part C	100	200
		All	100	770

3.4.2 Lexicographic choosers

The share of respondents consequently choosing the cheapest alternative is 45% in the car experiment, 20% in the single-mode PT experiment, and 4% in the multiple-mode PT experiment. To interpret these shares, we must somehow assess the significance of always choosing the cheaper alternative. For this, we compare with a random lottery.

Say that all respondents choose the cheaper alternative with probability p, and that all choices are independent. In that case, if the probability of choosing the cheaper alternative eight times out of eight (p^{-8}) was 45%, we would have p =91%. Hence, the share of 45% “always-cheaper” respondents in the car game is rather high – it corresponds to a random lottery with a 91% probability of choosing the cheaper alternative.

Similarly, a 20% (4%) probability of being “always-cheaper” in eight out of eight choices corresponds to p =82% (67%).

For the car game and the PT single-mode game the p's are rather large, indicating that shares of “always-cheaper” are too large to be a mere coincidence. Hence in these experiments we do have a rather large group of people always rejecting to pay for improvements.

For comparison with SP1, the share of car users always choosing the cheapest alternative in SP1 was 17%, which corresponds to p = 80%.

3.5 What can be estimated from the three experiments

The experimental design and the nature of data determine which time values can be estimated from the experiments.

By design, the number of interchanges is correlated with the associated interchange waiting time. When there are no interchanges, the interchange waiting time is zero. With one or more interchanges, the average interchange waiting time increases with the number of interchanges. Hence identification relies on our assumption of constant unit values of interchanges and interchange waiting time. Without this assumption, we would not be able to distinguish the value of zero interchanges from the value of zero waiting time.

This is a potential problem in the multiple-mode PT experiment, where all alternatives have zero or one interchange. Since these data sets are rather small, it may be difficult to separate the effect of an interchange from the effect of waiting time. As mentioned in section 2.5, a separate parameter for interchanges cannot be estimated for part A – hence when part A is estimated separately the corresponding variable t^{ch} is omitted from the model[10].

As mentioned in section 2.3, to identify reference-dependence it is necessary that the attributes vary sufficiently around the references. We now investigate each time component separately to check if this is the case.

In the car experiment, parking time is included for only 336 of the 1437 respondents, and of these 263 have a reference parking time of zero minutes. Hence the distribution of differences $t^{pk} - t_0^{pk}$ is very asymmetric with almost all its mass on the non-negative axis (see Figure 1 below). We therefore do not attempt to estimate reference-dependence for parking time.

[10] This is the case in the initial models.

Figure 1: Distribution of parking time differences (only respondents who are presented with parking time in the experiment*).

* The difference is always zero for respondents who are not presented with parking time in the experiment.

In the single-mode public transport game, there are similar problems with the number of interchanges and waiting time. Most respondents do not experience any interchanges on their reference trip, and very few experience more than one interchange. Hence, as shown in Table 6, the shares of negative interchange differences $t^{ch} - t_0^{ch}$ and negative waiting time differences $t^{wt} - t_0^{wt}$ are very low for metro and S-train, and rather low for bus and train. We omit reference-dependence with regard to the number of interchanges, and reference-dependence with regard to interchange waiting time is included only for bus and train.

Table 6: Single-mode PT: Distribution of differences between attribute and reference values for interchange waiting time and number of interchanges.

	Bus	Metro	S-train	Train
Share of negative interchange differences ($t^{ch} - t_0^{ch}$)	5.8%	0.3%	2.5%	4.9%
Share of negative interchange waiting time differences ($t^{wt} - t_0^{wt}$)	9.2%	0.3%	2.6%	8.6%

There are similar problems in the multiple-mode experiment. Again the variation in number of interchanges is too small to estimate reference-dependence. Also the low variation in interchange waiting time differences is likely to make identification of interchange waiting time reference-dependence impossible.

Due to the time constraints, and because the results from the single-mode and the multiple-mode experiments are meant to supplement each other, we have decided not to include reference-dependence in the multiple-mode models.

It is essential for the interpretation of the results to consider the impacts of not being able to control for loss aversion when the attributes do not vary sufficiently around the reference. If almost all differences $t^i - t_0^i$ are non-negative, the alternatives are worse than the reference, and the time values inferred are willingness-to-accept (WTA) values. If the differences are almost always non-positive, the time values are willingness-to-pay (WTP) values. We expect WTA values to be higher than the "reference-free" value, and WTP values to be lower (due to loss aversion).

For the car segment, omitting a reference-dependence parameter for parking time implies that the estimated value of parking time should be interpreted as a WTA value. The same goes for the omitted parameters in the single-mode public transport experiment. For the multiple-mode experiment, there are no positive interchange differences ($t^{ch} - t_0^{ch}$), hence the inferred value of interchanges should be interpreted as WTP values.

4 Results

All estimations were carried out in Biogeme, a software package designed for the maximum likelihood estimation of Generalized Extreme Value (GEV) models.[11] We use 300 Halton draws per individual to simulate the likelihood contribution.

4.1 Car game

The estimated parameters of the base model and the models with reference-dependent preferences are shown in Table 36- Table 38 in the Appendix. The log likelihood values are given in Table 7 below.

In the base model, all parameters are significant at the 1% level. In the model with reference-dependent preferences, the reference-dependence parameter η_{cng} for congested driving time is very insignificant, and hence we omit it from the model. In the resulting model (Table 38), reference-dependence for free-flow driving time (η_{ff}) is significant at the 10% level, and the remaining parameters at the 1% level. All η's are positive, indicating loss aversion.

A likelihood ratio test comparing the model with reference-dependent preferences to the base model reveals that the former is significantly better (the p-value is less than 10^{-5}).

Table 7: Summary of car models

Model	Log likelihood	#Parameters	#Obs.
Base model	-3358.43	6	7888
Reference-dependent preferences for cost, free-flow, congested and egress walk time.	-3343.42	10	7888
Reference-dependent preferences for cost, free-flow, and egress walk time.	-3344.39	9	7888
Distance-specific parameters.	-3317.57	14	7888
Distance-specific value of free-flow time.	-3320.84	11	7888

[11] See Bierlaire (2003), Bierlaire (2005), or http://roso.epfl.ch/biogeme

Table 40 gives the estimated parameters of the model with distance-specific parameters. Except for α_{cng}^{S}, all parameters are significant. The parameters for the short trips differ considerably from those of the long trips. However, the likelihood ratio test of common α's for short and long trips is accepted when testing at the 1% level (p-value: 8.8%). In the model with common α's only the (random) value of free-flow driving time is distance-specific. The estimated parameters of this model are given in Table 41 in the Appendix.

Following the methodology in Fosgerau and Bierlaire (2005), we estimate a model in which the distribution of the random term u_n is a transformation of the normal distribution. Since this generalised distribution has the normal distribution as a special case (with the transformation equal to the identity transformation), we are able to test how well the assumption of lognormal VTT fits our data, and how it affects the relative values of travel time components. Since our estimation software only allows one random parameter to follow such a generalised distribution, we shall not apply the test to the model with distance-specific value of free-flow time (in which the value of free-flow time has two different distributions – one for short trips and another for long). Instead we apply the test to the model with reference-dependent preferences for cost, free-flow and egress walk time, and a common value of free-flow time for all distances.

Table 8 compares the model with generalised VTT distribution to the model with lognormal VTT. The former is significantly better, indicating that the VTT is not lognormal.[12] However, the α's and η's are practically unaffected of the choice of distribution (see estimated parameters in Table 38 and Table 39). We therefore conclude that the models with lognormal VTT are acceptable for the purpose of obtaining relative values of time components.

Table 8: Car models, VTT distribution lognormal or generalised.

Model	Log Likelihood	#Parameters	#Obs.
Lognormal VTT	-3344.39	9	7888
Generalised VTT distribution	-3336.82	12	7888

The time values are thus computed using the results from the model with distance-specific value of free-flow time, common α's for all distances and lognormal VTT (Table 41). The resulting time values are shown in Table 9 below. The value of free-flow driving time is the expectation of $\exp(u)$,

[12] Notice that the non-normal VTT for the car segment corresponds exactly to the findings in SP1.

which is $\exp(\bar{u}+\sigma^2/2)$ when u is distributed lognormal $(\bar{u},\sigma^2)$. The relative values of time are computed as $\exp(\alpha_i)$, with confidence intervals [$\exp(\alpha_i - 2\text{std.err.}(\alpha_i))$; $\exp(\alpha_i + 2\text{std.err.}(\alpha_i))$]. This confidence interval is based on the asymptotic normality of the estimated parameters, and should be interpreted with caution, as the approximation to the normal distribution is not expected to be very good for non-linear models as the ones in the current analysis.

Recall from section 2.1.2 that the value of the *i*'th time component is $\exp(\alpha_i)$ times the value of free-flow time. Hence a relative value of 1.85 (for parking time) means that parking time is worth 85% more than free-flow time.

Note that, the official value of free-flow driving time to be used in economic evaluation will be based on the results of experiment 1 (SP1). Hence the reported value of free-flow time will not be used, and is reported only to show that the level is reasonable. When comparing to the values of SP1, one need to take into account the distributional assumptions of the models: In SP1 we use a generalised VTT distribution instead of the lognormal, which results in a more right-skewed distribution and a much higher mean.

Table 9: Time values for the car segment

Value of free-flow driving time	DKK/minute	DKK/hour
Trip length <= 25 km.	1.64	98
Trip length > 25 km.	1.29	78
Relative values of time with confidence intervals (unit is value of free-flow time)		
Congested driving time	0.88	[0.81 ; 0.97]
Egress walk time	1.55	[1.37 ; 1.76]
Parking time	1.85	[1.59 ; 2.15]

We find that time spent searching for a parking place is valued almost twice as high as free-flow driving time, and that time spent walking to/from the car is valued around 50% higher. These results seem reasonable. The high value of parking search time may be partly due to the fact that it is a WTA value, as mentioned in section 3.5. Another reason could be that respondents experience parking time as connected with some uncertainty, even though the attribute values in the experiment are certain amounts.

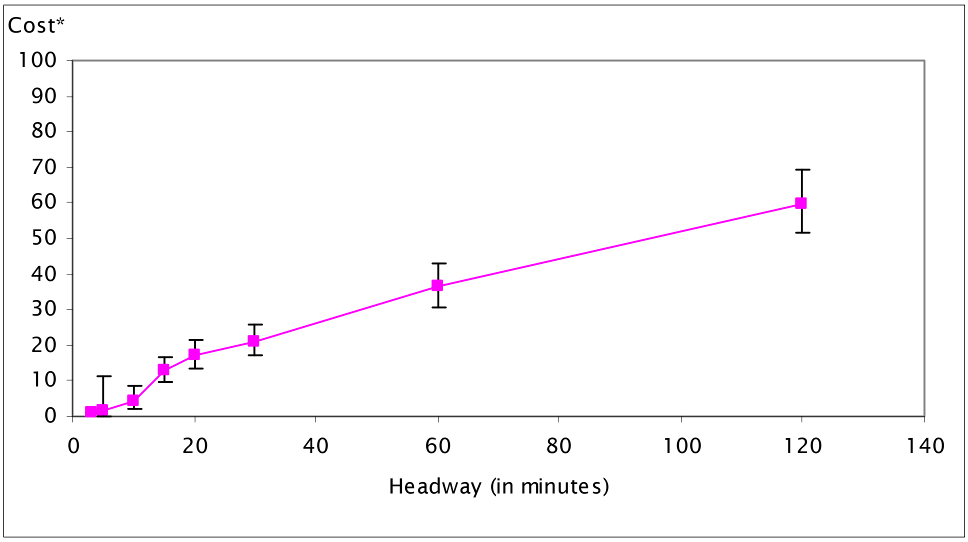
The estimated value of congested driving time is less than the value of free-flow time, which is clearly an undesirable result, as it is inconsistent with theory and findings from other studies.[13]

4.2 PT Single-mode game

4.2.1 Headway formulation

We start by examining the results of the model with headway dummies (eq. 9 for bus, S-train and train, and eq. 7 for metro). For metro, α_{hdw5} is not identified, and we therefore drop the dummy for headway level 5 minutes. This corresponds to assuming that a headway value of 5 minutes is worth the same as a headway value of "less than 5 minutes" (the base). The estimated parameters are listed in Table 43 in the Appendix. The resulting headway costs (with confidence limits) are shown below[14].

Figure 2: Bus headway cost with confidence limits (Single-mode exp.)

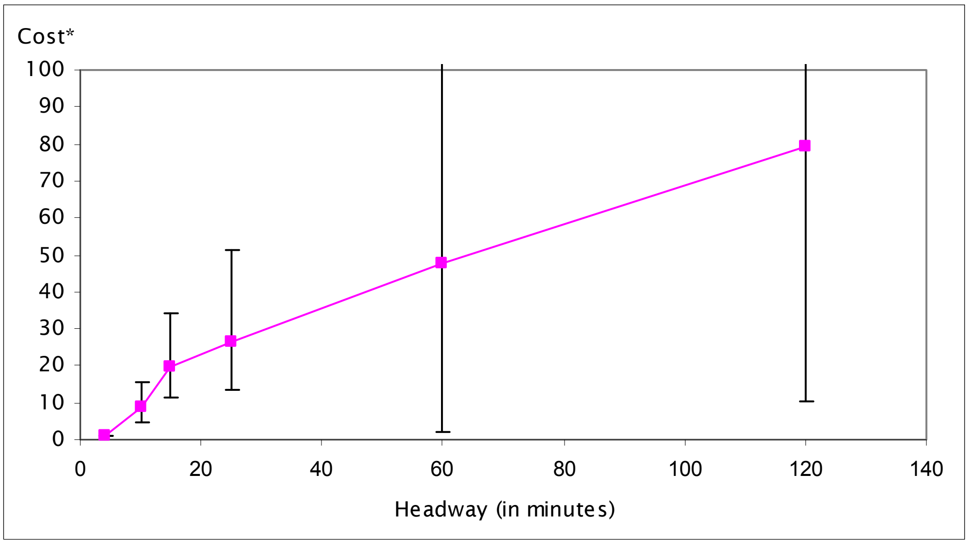


* The unit is value of in-vehicle time, hence a headway level of 60 minutes is worth roughly the same as 30-40 minutes of in-vehicle time.

[13] See e.g. Wartburg and Waters (2004)

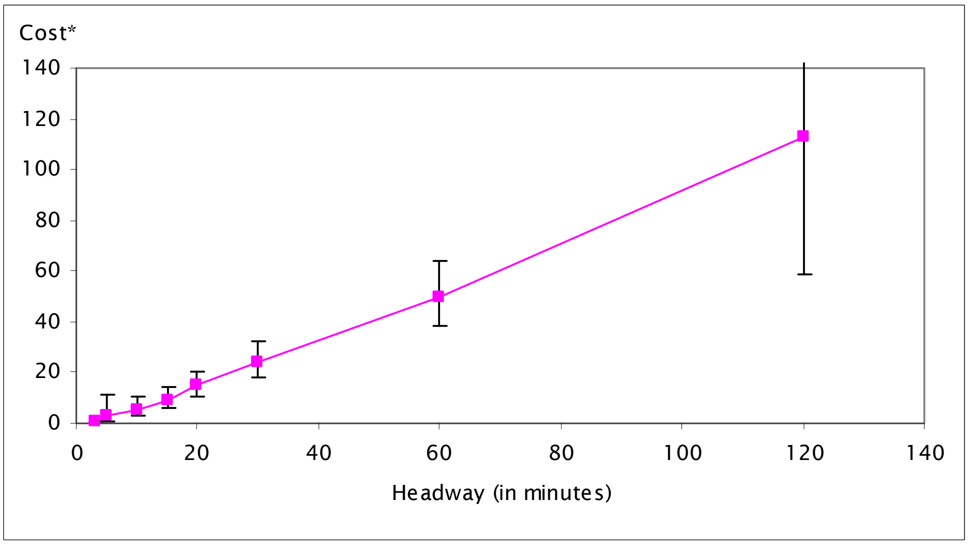
[14] The depicted headway costs are for respondents whose headway reference is not missing.

Figure 3: Metro headway cost with confidence limits (Single-mode exp.)



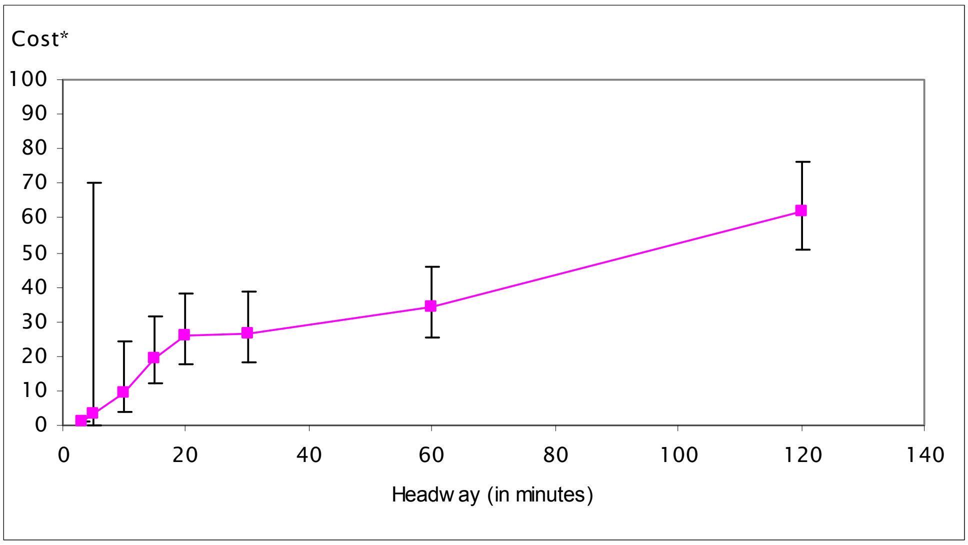
* The unit is value of in-vehicle time, hence a headway level of 15 minutes is worth roughly the same as 20 minutes of in-vehicle time.

Figure 4: S-train headway cost with confidence limits (Single-mode exp.)



* The unit is value of in-vehicle time, hence a headway level of 60 minutes is worth roughly the same as 40-50 minutes of in-vehicle time.

Figure 5: Train headway cost with confidence limits (Single-mode exp.)



* The unit is value of in-vehicle time, hence a headway level of 60 minutes is worth roughly the same as 30-40 minutes of in-vehicle time.

The figures support our belief that the marginal value of headway is lower for high headway levels than for low. To investigate this further, we estimate models where the generalised cost as a function of headway is piecewise linear with one slope when headway is below a threshold H^*, and another slope when it is above H^* (eq. 10). For each mode segment we estimate five models, with H^* = 10, 15, 20, 30, and 60 minutes. Table 10 gives a summary of these models for bus, S-train, and train.

Table 10: Summary of models with piecewise linear headway

Segment	Model	Log likelihood	#Parameters	#Obs
Bus	Headway dummies	-3611.96	15	7472
	H^*=10 minutes	-3629.22	10	7472
	H^*=15 minutes	-3618.16	10	7472
	H^*=20 minutes	-3614.86	10	7472
	H^*=30 minutes	-3620.64	10	7472
	H^*=60 minutes	-3629.05	10	7472
S-train	Headway dummies	-798.792	15	1822
	H^*=10 minutes	-799.12	10	1822
	H^*=15 minutes	-799.124	10	1822
	H^*=20 minutes	-799.365	10	1822
	H^*=30 minutes	-799.471	10	1822
	H^*=60 minutes	-799.435	10	1822
Train	Headway dummies	-1612.46	15	3337
	H^*=10 minutes	-1622.28	10	3337
	H^*=15 minutes	-1618.23	10	3337
	H^*=20 minutes	-1618.43	10	3337
	H^*=30 minutes	-1626.95	10	3337
	H^*=60 minutes	-1628.38	10	3337

The choice of H^* makes little difference for the S-train segment, where the model with headway dummies yields an almost linear headway cost (Figure 4). For the remaining segments, however, there are quite large differences in likelihood for different values of H^*. For the following models, we choose the value of H^* that yields the highest likelihood (this model is always accepted against the model with headway dummies when testing at the 1% level). The chosen values are listed in the table below.

Segment	H^*
Bus	20 minutes
S-train	10 minutes
Train	15 minutes

The estimated parameters of the models with piecewise linear headway are shown in Table 44 in the Appendix (for the chosen value of H^*). For bus and train, the marginal value of headway is higher for low headway levels than for high, as we expected. For the S-train segment, the parameters are not significantly different. The “correction” parameters for missing headway reference are negative, indicating that respondents who do not know the headway of their transport mode value headway levels of 60 minutes and 120 minutes lower than other people. A likely explanation is that respondents put very little weight on – or simply ignore - attributes that appear unrealistic. The parameters are not always significant, but we keep them throughout the analysis, as we are not interested in their value, but only need them to correct for unwanted effects.

For metro, we estimated models with piecewise linear headway and a single dummy for missing headway reference. The models are summarised in Table 11 below. The models are not always identified, and none of them are significantly better than the base model. The dummy for missing headway is always insignificant, as are the parameters of access/egress time, interchanges, and headway. We also estimate a model with linear headway and a single dummy for missing headway. This model is also not identified, and not significantly better than the base model. We therefore abandon the more complicated headway formulations, and simply keep the base model.

Table 11: Summary of metro models with different headway formulations

Model	Log likelihood	#Parameters	#Obs	
Base model	-367.693	7	843	
Headway dummies (no dummy for missing headway reference)	-368.268	11	843	
Piecewise linear headway ($H*$=10 minutes)	-367.663	9	843	*)
Piecewise linear headway ($H*$=15 minutes)	-366.847	9	843	*)
Piecewise linear headway ($H*$=20 minutes)	-366.835	9	843	
Piecewise linear headway ($H*$=30 minutes)	-366.444	9	843	
Linear headway	-367.677	8	843	*)

*) Not identified

Remark: The models with linear and piecewise linear headway are not nested within the model with headway dummies, as the latter has a common dummy for headway levels <5 and 5, a common dummy for levels 20 and 30, and no dummy for missing headway reference.

4.2.2 Reference-dependent preferences

We now generalise our model further by allowing for reference-dependence as described in section 2.3. For bus, S-train, and train, reference-dependence is added to the best model with piecewise linear headway (split at the chosen values of $H*$), while for metro it is added to the base model. Based on the discussion in section 3, we estimate models with reference-dependent preferences for cost, in-vehicle time, access/egress time, headway and interchange waiting time for the bus and train segments. For metro and S-train, we include reference-dependence for cost, in-vehicle time, access/egress time, and headway.

For bus, all reference-dependence parameters (η) are identified, and all but η_{wt} (corresponding to interchange waiting time) are significant. For metro, the only significant η is that of access/egress time, and for S-train only the η's of cost and access/egress time are significant. For train η_{wt} is not identified.

As a consequence, we leave out reference-dependence with regard to interchange waiting time completely. For metro and S-train, we leave out all insignificant reference-dependence parameters. The resulting model estimates are shown in Table 45 in the Appendix. All η's are positive, which indicates loss aversion. Their size vary from 0.17 to 0.48, meaning that a change from the reference is worth 1.4 – 2.6 times more if it is a loss than if it is a gain. Loss aversion with regard to cost is smaller than loss aversion regarding to time components.

For metro, the model with reference-dependent access/egress time is the final model. We summarise the relevant metro models in Table 12. Recall that three models are nested: The base model is a special case of the model with reference-dependent access/egress time, which is again a special case of the model with additional reference-dependence parameters.

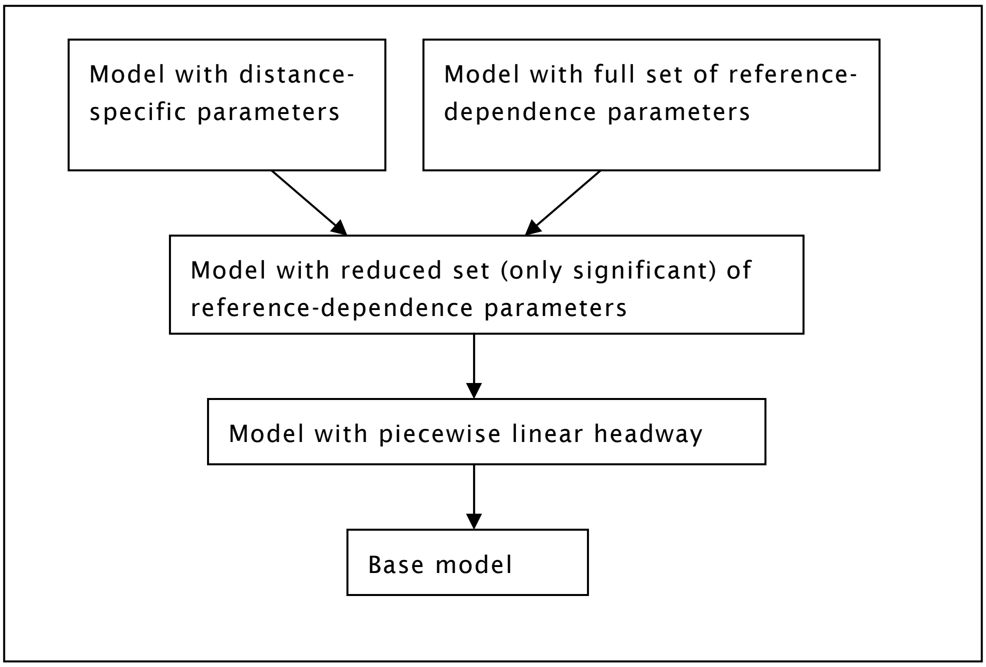
Table 12: Summary of metro models

Model	Log likelihood	#Parameters	#Obs.
Base model	-367.693	7	843
Reference-dependent preferences for cost, access/egress time, in-vehicle time, and headway.	-363.089	11	843
Reference-dependent preferences for access/egress time.	-364.16	8	843

4.2.3 Distance-specific parameters

For bus, S-train and train, we now allow parameters to depend on distance: Distance-specific parameters are incorporated into the models with a reduced set of reference-dependence parameters (Table 45). The nesting relations between models are shown in Figure 6 below.

Figure 6: Nesting structure (A→ B denotes “B is a special case of A”).



The estimated parameters of the model with distance-specific parameters are given in Table 47 in the Appendix.

What is of interest is testing if short- and long-distance parameters are significantly different. A likelihood ratio test of reducing the model with distance-specific parameters to the previous model is accepted for bus (p-value: 50%) and S-train (p-value: 13%), but strongly rejected for the train segment (p-value ≈ 10^{-8}). A summary of the relevant models is given in Table 13-Table 15.

Table 13: Summary of bus models

Model	Log likelihood	#Parameters	#Obs.
Base model	-3649.09	7	7472
Piecewise linear headway (split at 20 min)	-3614.86	10	7472
Reference-dependent preferences for cost, access/egress time, in-vehicle time, inter-change waiting time, and headway.	-3578.38	15	7472
Reference-dependent preferences for cost, access/egress time, in-vehicle time, and headway.	-3578.55	14	7472
Distance-specific parameters.	-3575.38	21	7472

Table 14: Summary of S-train models

Model	Log likelihood	#Parameters	#Obs.
Base model	-814.749	7	1822
Piecewise linear headway (split at 10 min)	-799.12	10	1822
Reference-dependent preferences for cost, access/egress time, in-vehicle time, and headway.	-790.917	14	1822
Reference-dependent preferences for cost and access/egress time.	-791.264	12	1822
Distance-specific parameters.	-785.678	19	1822

Table 15: Summary of train models

Model	Log likelihood	#Parameters	#Obs.
Base model	-1634.7	7	3337
Piecewise linear headway (split at 15 min)	-1618.23	10	3337
Reference-dependent preferences for cost, access/egress time, in-vehicle time, and headway.	-1599.48	14	3337
Distance-specific parameters.	-1574.19	21	3337
Distance-specific parameters. (Restriction: $\alpha^L_{hdwHIGH} = \alpha^S_{hdwHIGH}$)	-1574.21	20	3337
Distance-specific parameters. (Restriction: $\alpha^L_{hdwHIGH} = \alpha^S_{hdwHIGH}$, $\alpha^L_{wt} = \alpha^S_{wt}$)	-1577.8	19	3337
Distance-specific parameters. (Restriction: $\alpha^L_{hdwHIGH} = \alpha^S_{hdwHIGH}$, $\alpha^L_{wt} = \alpha^S_{wt}$, $\alpha^L_{hdwLOW} = \alpha^S_{hdwLOW}$)	-1579.08	18	3337
Distance-specific parameters. (Restriction: $\alpha^L_{hdwHIGH} = \alpha^S_{hdwHIGH}$, $\alpha^L_{wt} = \alpha^S_{wt}$, $\alpha^L_{hdwLOW} = \alpha^S_{hdwLOW}$, $\alpha^L_{ch} = \alpha^S_{ch}$)	-1579.14	17	3337
Distance-specific parameters. (Restriction: $\alpha^L_{hdwHIGH} = \alpha^S_{hdwHIGH}$, $\alpha^L_{wt} = \alpha^S_{wt}$, $\alpha^L_{hdwLOW} = \alpha^S_{hdwLOW}$, $\alpha^L_{ch} = \alpha^S_{ch}$, $\alpha^L_{ae} = \alpha^S_{ae}$)	-1582.81	16	3337

For the train segment, we want to check whether some of the alphas can be equal for short-distance and long-distance trips. First, we use Wald tests to investigate each time component separately by testing hypotheses of the form $H_0 : \alpha^L_i = \alpha^S_i$, where *i* denotes the time value in question. The results are shown in Table 52 in the Appendix. Then we turn to simultaneous hypotheses that involve several time components, e.g. $H_0 : \alpha^L_{hdwHIGH} = \alpha^S_{hdwHIGH}, \alpha^L_{wt} = \alpha^S_{wt}$. These are tested using likelihood ratio tests: We begin by estimating a model in which a single pair of alphas is restricted to be equal; if this model is accepted, we define another in which we further restrict a second pair of alphas, and so on. We use the results from Table 52 to determine the test sequence: Since the pair most likely to be equal is $\alpha^L_{hdwHIGH}, \alpha^S_{hdwHIGH}$, we first impose the restriction $\alpha^L_{hdwHIGH} = \alpha^S_{hdwHIGH}$. This causes a very small drop in likelihood, and is easily accepted with a likelihood ratio test (p-value: 84%). We then add the constraint $\alpha^L_{wt} = \alpha^S_{wt}$. This has a much larger effect on the likelihood, and is rejected by a likelihood ratio test against the model with the restriction $\alpha^L_{hdwHIGH} = \alpha^S_{hdwHIGH}$ (p-value: 0.7%). However, it is accepted against the unrestricted model (p-value: 2.7%), and since the standard deviation of α^L_{wt} is extremely large, we decide to accept the restriction.

The restrictions $\alpha^L_{hdwLOW} = \alpha^S_{hdwLOW}$, and $\alpha^L_{ch} = \alpha^S_{ch}$ are accepted both against the unrestricted model and against the previously accepted model. The following restriction $\alpha^L_{ae} = \alpha^S_{ae}$ is rejected with a p-value of 0.4% against the unrestricted model, and a p-value of 0.7% against the previously accepted model.

We conclude that, except for the value of in-vehicle time and access/egress time, there are no significant differences between time values for long and short trips. The estimated parameters of the model with distance-specific in-vehicle and access/egress time are presented in Table 48.

4.2.4 Generalised VTT distribution

As for the car segment, we test how the assumption of lognormal VTT affects the relative values of the time components. We estimate models where the random terms u_n follow a distribution that is a generalisation of the normal distribution. We would like to apply the generalised distribution to the best model so far, which is the reduced reference-dependent preferences model for bus, metro, and S-train, and the model with distance-specific preferences for the train segment. However, as mentioned in section 4.1, it is not straightforward to estimate a model where two random terms follow generalised distributions, so instead we apply the test to the reduced reference-dependent preferences model for all segments.

Table 16 summarises the relevant models. For metro, S-train, and train, the model with generalised VTT distribution is not significantly better than the model with lognormal VTT. Hence for these we can assume that VTT has a lognormal distribution. For bus, the generalised VTT distribution is significantly better than the lognormal, so we may not assume a lognormal VTT. However, the α's do not change with the choice of distribution (compare Table 45 (bus) with Table 46), so for our purpose we settle with the model with lognormal VTT.[15]

[15] Notice that as for the car segment the non-normal VTT segments correspond exactly to the findings in SP1.

Table 16: Lognormal and generalised VTT distribution.

Segment	Model	Log likelihood	#Parameters	#Obs
Bus	Lognormal VTT	-3578.55	14	7472
	Generalised VTT dist.	-3571.83	17	7472
Metro	Lognormal VTT	-364.16	8	843
	Generalised VTT dist.	-362.5	11	843
S-train	Lognormal VTT	-791.264	12	1822
	Generalised VTT dist.	-790.649	15	1822
Train	Lognormal VTT	-1599.48	14	3337
	Generalised VTT dist.	-1598.36	17	3337

4.2.5 Time values

Based on our analysis, we conclude that the values of time should be computed using the estimated parameters of the following models:

Mode	Final model
Bus	Model with piecewise linear headway (splits at 20 min.), and reference-dependent preferences for cost, access/egress time, in-vehicle time, and headway.
Metro	Model with linear headway and reference-dependent preferences for access/egress time.
S-train	Model with piecewise linear headway (splits at 10 minutes) and reference-dependent preferences for cost and access/egress time.
Train	Model with piecewise linear headway (splits at 15 minutes), with distance-specific parameters for in-vehicle time and access/egress time, and with reference-dependent preferences for cost, access/egress time, in-vehicle time, and headway.

The resulting time values are shown in Table 17 below. They are computed as described on page 28 for the car time values, and the comment regarding the confidence intervals should be kept in mind. Recall that the purpose of our analysis is to obtain relative time values and that the official value of in-vehicle time to be used in evaluations will be inferred from SP1; hence the reported values of in-vehicle time are only mentioned to show that the model makes reasonable estimates.

Table 17: Time values for the PT single mode game

	Bus	Metro	S-train	Train	
Trip length				<= 50 km.	>50 km.
H^* (minutes)	20		10	15	15
Value of in-vehicle time					
DKK/minute	0.62	1.00	0.90	0.87	2.88
DKK/hour	37	60	54	52	173
Relative values of time					
Access/egress time	**1.77**	**1.32**	**1.26**	**1.29**	**0.88**
Confidence Interval	*[1.41 ; 2.22]*	*[0.82 ; 2.11]*	*[0.98 ; 1.61]*	*[1.01 ; 1.65]*	*[0.66 ; 1.17]*
Interchanges	**12.23**	**1.55**	**5.18**	**12.92**	
Confidence Interval	*[9.04 ; 16.53]*	*[0.08 ; 31.47]*	*[2.41 ; 11.13]*	*[8.63;19.36]*	
Headway ($\leq H^*$)	**1.09**	**1.32**	**0.70**	**1.59**	
Confidence Interval	*[0.84 ; 1.41]*	*[0.81 ; 2.16]*	*[0.36 ; 1.38]*	*[0.9 ; 2.83]*	
Headway ($> H^*$)	**0.45**	**1.32**	**0.93**	**0.38**	
Confidence Interval	*[0.36 ; 0.56]*	*[0.81 ; 2.16]*	*[0.72 ; 1.21]*	*[0.31 ; 0.48]*	
Interchange waiting time	**1.96**	**2.45**	**1.86**	**1.40**	
Confidence Interval	*[1.47 ; 2.61]*	*[1.46 ; 4.1]*	*[1.32 ; 2.63]*	*[0.87;2.27]*	

For metro, S-train, and short train trips, the value of access/egress time is about 30% more than the value of in-vehicle time. For bus the relative value is a little higher, while for long train trips it is lower than the value of in-vehicle time.

The value of an interchange seems to depend very much on the type of mode: For high-frequency modes as metro and S-train an interchange is worth the same as 1.5 and 5.2 minutes of in-vehicle time, respectively, while for bus and train its value is equivalent to 12-13 minutes of in-vehicle time.

Except for S-train, the price of an extra minute between departures is equivalent to 1.1-1.6 minutes of in-vehicle time, up to a certain point, after which it drops to 0.4 minutes (for metro, there is no such threshold, as high headway values are unrealistic). For S-train, the price is 0.7 minutes up to the threshold, after which it is 0.9 minutes. However, these values are not significantly different, and we may assume, as for metro, that the value of headway is constant for all headway levels. Possibly this is because S-train is also a high-frequency mode, such that data contain few high headway levels.

For bus and train, low headway levels are valued at a higher marginal rate than high levels, possibly because departures are so frequent that people do not bother to plan their arrival at the station/stop, meaning that the extra time between departures cannot be used for other purposes.

The value of waiting time associated with interchanges differs a lot between modes: From 1.4 to 2-5 minutes of in-vehicle time.

As for the general level of time values, respondents on long train trips have the highest value of time, while people taking the bus have the lowest[16]. This is in agreement with the results from SP1.

4.3 PT Multiple-mode game

For the multiple-mode, we estimate the base model with separate parameters for part A and parts B and C (eqs. (13) and (14)). The estimated parameters of the base model are shown in Table 49.

For each parameter, we test whether the parameter can have the same value in part A as in parts B and C. Again, we use Wald tests, and test the restrictions $\alpha_i^A = \alpha_i^{BC}$ one by one in the base model. The tests are summarised in Table 53 in the Appendix.

For the two small segments, bus-metro and metro-train, it does not seem unrealistic that parameters are the same in part A and parts B and C. This is indeed the case: Models with common parameters are accepted against the base model for both segments (p-values 19% and 11%, respectively). Table 18 below summarises the relevant models.

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[16] Here we do not take account of the fact that the value of time should be computed using a generalised VTT distribution for the bus segment. However, in SP1 introducing a generalised distribution decreases the mean VTT for the bus segment.

Table 18: Summary of bus-metro and metro-train models

Segment	Model	Log likelihood	#Parameters	#Obs
Bus-Metro	Base model	-331.279	14	797
	Common Parameters	-335.643	8	797
Metro-Train	Base model	-511.309	14	1137
	Common Parameters	-516.554	8	1137

For the bus-train segment, the Wald tests indicate that some parameters can be combined, but not the scale. We proceed in the same way as in section 4.2.3, imposing restrictions one at time, and always choosing the one with highest test probability in the Wald tests. All models are summarised in Table 19 below.

Table 19: Summary of bus-train models

Model	Log likelihood	#Parameters	#Obs.
Base model (separate time values and error scale in part A and parts B and C)	-1808.03	14	4100
Restricting $\alpha_{wt}^{A} = \alpha_{wt}^{BC}$ in above model	-1809.11	13	4100
Restricting $\alpha_{hdw}^{A} = \alpha_{hdw}^{BC}$ in above model	-1810.18	12	4100
Restricting $\alpha_{ivTrain}^{A} = \alpha_{ivTrain}^{BC}$ in above model	-1812.20	11	4100
Restricting $\alpha_{ae}^{A} = \alpha_{ae}^{BC}$ in above model	-1814.34	10	4100
Restricting $\bar{u}^{A} = \bar{u}^{BC}$ in above model	-1814.88	9	4100
Common parameters (Restricting $\mu^{A} = \mu^{BC}$ in above model)	-1826.35	8	4100

Except for the model with common parameters, all models are accepted at the 1% level, both against the base model and against the previously accepted model. The model with common parameters is rejected against the base model with a p-value of approximately $2 \cdot 10^{-6}$, and against the previously accepted model (common time values, but separate scales) with a p-value of $1.7 \cdot 10^{-6}$.

Based on the above conclusions, the time values should be computed using the estimated parameters of the model with common parameters for bus-metro and metro-train segments, and the model with common time values and separate scale for the bus-train segment. The relevant parameters are shown in Table 50 and Table 51 in the Appendix, and the resulting time values are presented below. Again we refer to page 28 (car time values), for computation of relative time values and confidence intervals.

Table 20: Time values for the PT Multiple-mode game

	Bus-Metro	Bus-Train	Metro-Train
Base mode (for which corresponding in-vehicle time is the base time component)	Bus	Bus	Metro
Value of in-vehicle time in base mode			
DKK/minute	0.57	1.79	0.82
DKK/hour	34	107	39
Relative values of time*			
Access/egress time	**1.07**	**0.95**	**1.17**
Confidence Interval	*[0.72 ; 1.6]*	*[0.79 ; 1.14]*	*[0.81 ; 1.7]*
Interchanges	**8.54**	**5.54**	**8.65**
Confidence Interval	*[5.28 ; 13.82]*	*[3.28 ; 9.33]*	*[5.29 ; 14.14]*
Headway	**0.63**	**0.47**	**1.21**
Confidence Interval	*[0.38 ; 1.05]*	*[0.39 ; 0.56]*	*[0.84 ; 1.75]*
In-vehicle time in other mode	**0.79**	**0.79**	**0.88**
Confidence Interval	*[0.5 ; 1.22]*	*[0.7 ; 0.89]*	*[0.73 ; 1.07]*
Interchange waiting time	**1.07**	**1.39**	**1.67**
Confidence Interval	*[0.65 ; 1.78]*	*[1.11 ; 1.73]*	*[1.09 ; 2.54]*

*Notice that relative values are relative to values of in-vehicle time in the base mode.

From Table 20 we notice that bus in-vehicle time is more expensive than metro or train in-vehicle time, and that metro in-vehicle time is more expensive than train in-vehicle time. These are probably comfort effects, as we know from the single-mode experiment that train passengers usually have higher value of time than bus and metro passengers, with bus passengers as the lowest.

In general, the relative time values are lower than in the single-mode experiment: Access/egress time is worth the same as 1 - 1.2 minutes of in-vehicle time, the value of an interchange is 5.5 – 8.5 minutes, and the value of waiting time is 1.1 – 1.7 minutes. Our best explanation of the differences between the single-mode and multiple-mode experiments is that it is two different groups of respondents: Respondents participating in the multiple-mode experiment have used more than one public mode on the reference trip. Hence they may be more used to interchanges and interchange waiting time, and accordingly value them differently. (This argument may involve a degree of self-selection, as respondents who strongly dislike interchanges are not as likely to participate in the multiple-mode experiment).

For bus-metro and bus-train, headway is worth roughly half as much as a minute of in-vehicle time, while for metro-train it is worth 1.2 minutes. It seems the relative values are higher in the metro-train segment than the other, perhaps partly offsetting the low value of base in-vehicle time compared to the other segment including train passengers.

5 Conclusion

The time values obtained from SP2 are relative values of congested driving time, walking time, and parking time, for cars, and access/egress time, interchange waiting time, number of interchanges, and headway, for public transport.

Concerning car, we find that walking time is valued 55% higher than free-flow driving time, and parking time 85% higher. Contrary to theory and expectation, congested driving time is valued lower than free-flow driving time, though the difference is only just significant. However, when it comes to deciding on the official time values, we shall not recommend evaluating congested driving time at a lower rate than free-flow time. A possible recommendation could be to assign equal values to congested and free-flow time – this can be justified by the fact that the congested values stated in the experiment are certain values that does not contain a reliability component. Hence, if uncertainty is the major reason that congested time is usually valued higher, it would not show in this experiment.

The results for public transport modes differ across modes, but seem reasonable. Recommendations on how to apply the results in order to obtain values that can be used for economic evaluation are given in the final report of the Danish Value of Time Study (Fosgerau, Hjorth, Vincent Lyk-Jensen, 2007b).

6 References

Bierlaire, M. (2003). “BIOGEME: A free package for the estimation of discrete choice models”, *Proceedings of the 3rd Swiss Transportation Research Conference*, Ascona, Switzerland.

Bierlaire, M. (2005). ”An introduction to BIOGEME Version 1.4”, biogeme.epfl.ch.

De Borger, B. and M. Fosgerau (2006). ”Another test of the theory of reference-dependent preferences: The trade-off between money and time”, European Transport Conference 2006.

Caussade, S., J. Ortúzar, L. Rizzi, and D.A. Hensher (2005). “Assessing the influence of design dimensions on stated choice experiment estimates”, *Transportation Research B*, vol. 39, no. 7, pp. 621-640.

Fosgerau, M. and M. Bierlaire (2007). “A practical test for the choice of mixing distribution in discrete choice models“, *Transportation Research B,* 41, pp. 784-794.

Fosgerau, M., K. Hjorth, and S. Vincent Lyk-Jensen (2007a). “The Danish Value of Time Study, Results for experiment 1”, Danish Transport Research Institute, Note 5.

Fosgerau, M., K. Hjorth, and S. Vincent Lyk-Jensen (2007b). “The Danish Value of Time Study, Final report”, Danish Transport Research Institute, Report 5.

Horowitz, J. K., and K. E. McConnell (2002). “A Review of WTA/WTP Studies”, *Journal of Environmental Economics and Management*, 44, pp. 426-447.

Kahneman, D. and A. Tversky (1979). “Prospect Theory: An Analysis of Decision under Risk”, *Econometrica*, vol. 47, no. 2, pp. 263-292.

Tversky, A. and D. Kahneman (1991). “Loss Aversion In Riskless Choice: A Reference Dependent Model”, *Quarterly Journal of Economics*, Vol. 106, no. 4, pp. 1039-1061.

Wartburg, M. and W.G.Waters (2004). “Congestion Externalities and the Value of Travel Time Savings”, chapter 2 in *Towards Estimating the Social and Environmental Costs of Transportation in Canada - A report for Transport Canada*.

7 Appendix

7.1 Notation summary

c_1, c_2: the costs of alternative 1 and 2

t_1, t_2 : vectors of time components of alternative 1 and 2.

x: vector of covariates

u: random variable representing taste heterogeneity

t^{ff} : free-flow driving time, in minutes.

t^{cng} : congested driving time, in minutes.

t^{eg} : egress walk time (car), in minutes.

t^{pk} : parking time, in minutes.

t^{ae} : access/egress time (public transport), in minutes.

t^{hdw} : headway of first mode, in minutes.

t^{iv} : total in-vehicle time (single-mode experiment), in minutes.

t^{ch} : number of interchanges.

t^{wt} : total waiting time associated with interchanges, in minutes.

$t_j^{ivMODE1}$: in-vehicle time in first mode (multiple-mode exp.), in minutes.

$t_j^{ivMODE2}$: in-vehicle time in second mode (multiple-mode exp.), in minutes.

7.2 Dominant choices

We define the variables *Best alt (C)* and *Best alt (T)* to indicate which alternative is the better with respect to cost and time, respectively. Alternatives are labelled “Left” and “Right” instead of 1 and 2.

Best alt (C) takes the values

- “Equal costs” if the two alternatives have equal costs
- “Left” if left is cheaper
- “Right” if right is cheaper

Best alt (T) depends on all the time components of the alternatives. It takes the values

- "All times equal" if alternatives are identical for all components.
- "Left" if all components are better for the left alternative.
- "Right" if all components are better for the right alternative.
- "None" otherwise.

For the public transport games, there is a potential problem in identifying dominance, as the headway variables in some cases take the value zero. (This is a mistake in the design and the observations will be excluded.) When defining dominance in choices where one of the headways is zero, the headway information is not used. Hence, some of the dominant choices may be choices that are to be deleted anyway.

In the following tables the number of dominant choices is marked in red. The tables only encompass the respondents that we have analysed in SP1.

Table 21: Dominant choices in the car experiment

	Best alt (C)			
Best alt (T)	Equal costs	Left	Right	Total
All times equal		47	50	97
Left	485	1533	1496	3514
None	1196	2159	2279	5634
Right	467	1431	1474	3372
Total	2148	5170	5299	12,617

There are in total 4,052 dominated choices (32%) for the car experiment.

Table 22: Dominant choices in the single-mode PT experiment

	Best alt (C)			
Best alt (T)	Equal costs	Left	Right	Total
Left	186	993	935	2114
None	2279	5136	4818	12,233
Right	156	883	981	2020
Total	2849	7094	6816	16,367

In the single PT mode there are 2,316 dominant choices, i.e. 14%.

Table 23: Dominant choices for multiple-mode PT experiment (A)

	Best alt (C)			
Best alt (T)	Equal costs	Left	Right	Total
Left	23	92	99	214
None	458	1159	1164	2781
Right	23	147	101	271
Total	504	1398	1364	3266

In part A of the multiple PT modes there are 239 dominated choices, i.e. 7.31%.

Table 24: Dominant choices for multiple-mode PT experiment (B)

	Best alt (C)			
Best alt (T)	Equal costs	Left	Right	Total
Left	1		9	10
None	553	530	534	1617
Right		9		9
Total	554	539	543	1636

In part B of the multiple PT there is only one dominated choice, i.e. 0.06%.

Table 25: Dominant choices for multiple-mode PT experiment (C)

	Best alt (C)			
Best alt (T)	Equal costs	Left	Right	Total
Left	3	2	15	20
None	526	526	544	1596
Right	3	14	3	20
Total	532	542	562	1636

In part C of the multiple PT modes there are 11 dominated choices, i.e. 0.7%.

7.3 Multiplicative versus additive errors

In our initial analysis, we compared six different models for each mode segment. Three of the models (Model1m, Model2m, Model3m) are special cases of the base model defined in eqs. (2) and (3), each with a different parametrisation of the generalised costs. In Model1m, the time values are constant over the population, in Model2m they vary randomly, and in Model3m some of the variation is explained systematically using covariates (enters the model as described in eq. (1). The other three (Model1a, Model2a, Model3a) are the corresponding models with additive errors.

The generalised cost in the three models is given in Table 26 below.

Table 26: Parametrisations of generalised costs.

Model	Description	Generalised cost
Model1	Model with constant time values (no heterogeneity, no covariates)	$c_{nrj} + (w_1, w_2, w_3, ..., w_K) t_{nrj}$ $w_1 ... \ w_K$: constants
Model2	Model with random time values (no covariates)	$c_{nrj} + e^{u_n}(1, e^{\alpha_2}, e^{\alpha_3}, ..., e^{\alpha_K}) t_{nrj}$
Model3	Model with random time values, that depend on income	$c_{nrj} + e^{\beta' x_{nr} + u_n}(1, e^{\alpha_2}, e^{\alpha_3}, ..., e^{\alpha_K}) t_{nrj}$ x_{nr} : income variables

In the models with additive errors, choices were modelled as

$$y_{nr} = 1 \quad \Leftrightarrow \quad -GC_{nr1} + \frac{\varepsilon_{nr1}}{\mu} \geq -GC_{nr2} + \frac{\varepsilon_{nr2}}{\mu}$$

instead of eq. (3).

The income variables in Model3 are the log of net personal income, a dummy for missing income information, a dummy for low personal income, and a dummy for high personal income. The dummies are only included if there are enough observations to identify them; hence the number of parameters in Model3 varies from segment to segment.

Since a model with multiplicative errors and the corresponding model with additive errors are not nested, we cannot test them against each other with a formal likelihood ratio test. This is irrelevant, however, since the models contain the same number of parameters, and we can simply compare their likelihood values. The model with the higher likelihood fits the data better.

All estimations were carried out in Biogeme, a software package designed for the maximum likelihood estimation of Generalized Extreme Value (GEV) models.[17] In models 2 and 3 we use 300 Halton draws per individual to simulate the likelihood contribution.

Our results are shown in the tables below. For all data segments but one (bus-metro, part A), the models with multiplicative errors have much higher likelihood than the corresponding models with additive errors. For most segments, going from additive to multiplicative errors increases likelihood more than allowing for random time values and adding covariates.

Based on these findings, we conclude that, for our data, the multiplicative errors model is superior to the additive errors model.

Table 27: Initial models, car experiment

	Log likelihood		#Parameters	#Obs
	Additive errors	Multiplicative errors		
Model1	-4532.39	-3839.49	5	7888
Model2	-4174.94	-3358.43	6	7888
Model3	-4133.88	-3313.93	10	7888

Table 28: Initial models, PT single-mode experiment, bus

	Log likelihood		#Parameters	#Obs
	Additive errors	Multiplicative errors		
Model1	-4066.8	-3779.38	6	7472
Model2	-3947.06	-3649.09	7	7472
Model3	-3936.54	-3638.71	11	7472

Table 29: Initial models, PT single-mode experiment, metro

	Log likelihood		#Parameters	#Obs
	Additive errors	Multiplicative errors		
Model1	-430.608	-384.924	6	843
Model2	-388.427	-367.693	7	843
Model3	-384.612	-364.493	11	843

Table 30: Initial models, PT single-mode experiment, S-train

	Log likelihood		#Parameters	#Obs
	Additive errors	Multiplicative errors		
Model1	-895.726	-857.152	6	1822
Model2	-873.11	-814.749	7	1822
Model3	-871.594	-813.316	11	1822

[17] See http://roso.epfl.ch/biogeme

Table 31: Initial models, PT single-mode experiment, train

	Log likelihood		#Parameters	#Obs
	Additive errors	Multiplicative errors		
Model1	-1897.9	-1736.12	6	3337
Model2	-1855.51	-1634.7	7	3337
Model3	-1843.33	-1611.68	11	3337

Table 32: Initial models, PT multiple-mode exp., bus-metro, part A.

	Log likelihood		#Parameters	#Obs
	Additive errors	Multiplicative errors		
Model1	-161.396	-166.612	6	382
Model2	-161.127	-164.823	7	382
Model3	-158.547	-164.063	10	382

Table 33: Initial models, PT multiple-mode exp., bus-metro, parts BC

	Log likelihood		#Parameters	#Obs
	Additive errors	Multiplicative errors		
Model1	-180.853	-176.401	7	415
Model2	-175.896	-170.907	8	415
Model3	-174.766	-169.828	11	415

Table 34: Initial models, PT multiple-mode exp., bus-train, part A.

	Log likelihood		#Parameters	#Obs
	Additive errors	Multiplicative errors		
Model1	-1023.74	-906.679	6	1961
Model2	-999.99	-855.852	7	1961
Model3	-998.341	-854.469	10	1961

Table 35: Initial models, PT multiple-mode exp., bus-train, parts BC

	Log likelihood		#Parameters	#Obs
	Additive errors	Multiplicative errors		
Model1	-1142.35	-997.856	7	2139
Model2	-1075.99*	-950.383	8	2139
Model3	-1075.1*	-950.068	11	2139

* The estimation software considered these models unidentified.

Results from the metro-train segment are missing, as the models are not identified.

7.4 Estimation results – car game.

Table 36: Base model

Segment:	Car		
Model:	Base model		
Log. Likelihood:		-3358.4	
Number of Halton draws:		300	
Number of estimated parameters:		6	
Number of observations:		7888	
Number of individuals:		1437	
Parameter	**Estimate**	**Std err**	
α_{cng}	-0.1481	0.0465	***
α_{eg}	0.4234	0.0568	***
α_{pk}	0.5651	0.0722	***
σ	1.4419	0.0619	***
$\bar{u}$	-0.7900	0.0574	***
μ	11.2735	0.3287	***

Table 37: First model with reference-dependent preferences

Segment:	Car		
Model:	Model with ref-dep preferences for cost, free-flow, congested and egress walk time		
Log. Likelihood:		-3343.4	
Number of Halton draws:		300	
Number of estimated parameters:		10	
Number of observations:		7888	
Number of individuals:		1437	
Parameter	**Estimate**	**Std err**	
α_{cng}	-0.1825	0.0517	***
α_{eg}	0.3941	0.0617	***
α_{pk}	0.5658	0.0747	***
η_{c}	0.1176	0.0280	***
η_{cng}	0.0876	0.0649	
η_{eg}	0.2259	0.0765	***
η_{ff}	0.0804	0.0483	*
σ	1.4567	0.0633	***
$\bar{u}$	-0.7969	0.0585	***
μ	11.4664	0.3354	***

Table 38: Second model with reference-dependent preferences

Segment:	Car		
Model:	Model with ref-dep preferences for cost, free-flow, and egress walk time		
Log. Likelihood:		-3344.4	
Number of Halton draws:		300	
Number of estimated parameters:		9	
Number of observations:		7888	
Number of individuals:		1437	
Parameter	**Estimate**	**Std err**	
α_{cng}	-0.1600	0.0471	***
α_{eg}	0.3852	0.0613	***
α_{pk}	0.5500	0.0743	***
η_c	0.1174	0.0280	***
η_{eg}	0.2237	0.0765	***
η_{ff}	0.0840	0.0481	*
σ	1.4521	0.0630	***
$\bar{u}$	-0.7921	0.0582	***
μ	11.4552	0.3348	***

Table 39: Model with generalised VTT distribution

Segment:	Car		
Model:	Model with generalised distribution of u, and ref-dep preferences for cost, free-flow, and egress walk time.		
Log. Likelihood:		-3336.8	
Number of Halton draws:		300	
Number of estimated parameters:		12	
Number of observations:		7888	
Number of individuals:		1437	
Parameter	**Estimate**	**Std err**	
α_{cng}	-0.1516	0.0466	***
α_{eg}	0.3952	0.0606	***
α_{pk}	0.5565	0.0736	***
η_c	0.1196	0.0283	***
η_{eg}	0.2203	0.0760	***
η_{ff}	0.0832	0.0476	*
σ	1.6834	0.2705	***
$\bar{u}$	-1.1183	0.2956	***
μ	11.5055	0.3358	***
δ_1 *)	0.0879	0.0943	
δ_2 *)	0.0087	0.1209	
δ_3 *)	-0.1768	0.0544	***

*) Transformation parameters, see Fosgerau and Bierlaire (2005).
Lognormal VTT corresponds to $\delta_1 = \delta_2 = \delta_3 = 0$.

Table 40: Model with distance-specific parameters

Segment:	Car		
Model:	Model with distance-specific parameters.		
Log. Likelihood:		-3317.6	
Number of Halton draws:		300	
Number of estimated parameters:		14	
Number of observations:		7888	
Number of individuals:		1437	
Parameter	**Estimate**	**Std err**	
α_{cng}^{L}	-0.1886	0.0652	***
α_{cng}^{S}	-0.0677	0.0686	
α_{eg}^{L}	0.5666	0.0872	***
α_{eg}^{S}	0.3701	0.0798	***
α_{pk}^{L}	0.7106	0.1278	***
α_{pk}^{S}	0.5804	0.0932	***
η_{c}	0.1221	0.0281	***
η_{eg}	0.2524	0.0776	***
η_{ff}	0.0853	0.0474	*
σ^{L}	1.0505	0.0655	***
σ^{S}	1.8503	0.1232	***
$\bar{u}^{L}$	-0.2890	0.0589	***
$\bar{u}^{S}$	-1.2406	0.0969	***
μ	11.9267	0.3511	***

Table 41: Model with distance-specific u

Segment:	Car		
Model:	Model with distance-specific u		
Log. Likelihood:		-3320.8	
Number of Halton draws:		300	
Number of estimated parameters:		11	
Number of observations:		7888	
Number of individuals:		1437	
Parameter	**Estimate**	**Std err**	
α_{cng}	-0.1238	0.0463	***
α_{eg}	0.4390	0.0620	***
α_{pk}	0.6145	0.0748	***
η_{c}	0.1232	0.0282	***
η_{eg}	0.2584	0.0780	***
η_{ff}	0.0904	0.0474	*
σ^{L}	1.0381	0.0649	***
σ^{S}	1.8639	0.1240	***
$\bar{u}^{L}$	-0.2814	0.0575	***
$\bar{u}^{S}$	-1.2441	0.0927	***
μ	11.8829	0.3481	***

7.5 Estimation results – PT single-mode game.

Table 42: Base model

Segment:	PT Single-mode Bus		
Model:	Base model		
Log. Likelihood:		-3649.1	
Number of Halton draws:		300	
Number of estimated parameters:		7	
Number of observations:		7472	
Number of individuals:		1103	
Parameter	**Estimate**	**Std err**	
α_{ae}	0.5353	0.0778	***
α_{ch}	2.3852	0.1358	***
α_{hdw}	-0.7055	0.0766	***
α_{wt}	0.6168	0.1147	***
σ	1.2976	0.0843	***
$\overline{u}$	-1.2912	0.0896	***
μ	6.1485	0.1815	***

Segment:	PT Single-mode Metro		
Model:	Base model		
Log. Likelihood:		-367.69	
Number of Halton draws:		300	
Number of estimated parameters:		7	
Number of observations:		843	
Number of individuals:		126	
Parameter	**Estimate**	**Std err**	
α_{ae}	0.3044	0.2264	
α_{ch}	0.4410	1.4760	
α_{hdw}	0.3080	0.2432	
α_{wt}	0.8913	0.2548	***
σ	1.2663	0.2274	***
$\overline{u}$	-0.8356	0.2733	***
μ	6.9454	0.6040	***

Segment:	PT Single-mode S-train		
Model:	Base model		
Log. Likelihood:		-814.75	
Number of Halton draws:		300	
Number of estimated parameters:		7	
Number of observations:		1822	
Number of individuals:		264	
Parameter	**Estimate**	**Std err**	
α_{ae}	0.2670	0.1226	**
α_{ch}	1.6922	0.3748	***
α_{hdw}	-0.1539	0.1253	
α_{wt}	0.6560	0.1710	***
σ	1.1758	0.1385	***
$\overline{u}$	-0.8050	0.1475	***
μ	7.9536	0.4505	***

Segment:	PT Single-mode train		
Model:	Base model		
Log. Likelihood:		-1634.7	
Number of Halton draws:		300	
Number of estimated parameters:		7	
Number of observations:		3337	
Number of individuals:		503	
Parameter	**Estimate**	**Std err**	
α_{ae}	0.0647	0.0865	
α_{ch}	2.2768	0.2241	***
α_{hdw}	-1.0023	0.0857	***
α_{wt}	0.3048	0.2132	
σ	1.4834	0.1220	***
$\overline{u}$	-0.2313	0.1096	**
μ	7.1579	0.3033	***

Table 43: Models with headway dummies

Segment:	PT Single-mode Bus		
Model:	Model with headway dummies		
Log. Likelihood:		-3611.96	
Number of Halton draws:		300	
Number of estimated parameters:		15	
Number of observations:		7472	
Number of individuals:		1103	
Parameter	**Estimate**	**Std err**	
α_{ae}	0.5072	0.0748	***
α_{ch}	2.4191	0.1297	***
α_{hdw5}	0.4741	0.9646	
α_{hdw10}	1.4935	0.3429	***
α_{hdw15}	2.5527	0.1346	***
α_{hdw20}	2.8323	0.1129	***
α_{hdw30}	3.0430	0.1052	***
α_{hdw60}	3.5939	0.0827	***
α_{hdw120}	4.0910	0.0730	***
α_{wt}	0.5568	0.1131	***
β_{hdw60m}	-25.1494	28.1261	
$\beta_{hdw120m}$	-51.7775	30.7121	*
σ	1.2932	0.0826	***
$\bar{u}$	-1.2433	0.0869	***
μ	6.5631	0.2065	***

Segment:	PT Single-mode Metro		
Model:	Model with headway dummies		
Log. Likelihood:		-368.27	
Number of Halton draws:		300	
Number of estimated parameters:		11	
Number of observations:		843	
Number of individuals:		126	
Parameter	**Estimate**	**Std err**	
α_{ae}	0.3585	0.2355	
α_{ch}	0.4026	1.5908	
α_{hdw10}	2.1490	0.3019	***
α_{hdw15}	2.9841	0.2777	***
$\alpha_{hdw20-30}$	3.2655	0.3343	***
α_{hdw60}	3.8639	1.6082	**
α_{hdw120}	4.3746	1.0143	***
α_{wt}	0.9452	0.2647	***
σ	1.1888	0.2238	***
$\bar{u}$	-0.8880	0.2790	***
μ	6.3184	0.5521	***

Segment:	PT Single-mode S-train		
Model:	Model with headway dummies		
Log. Likelihood:		-798.79	
Number of Halton draws:		300	
Number of estimated parameters:		15	
Number of observations:		1822	
Number of individuals:		264	
Parameter	**Estimate**	**Std err**	
α_{ae}	0.1971	0.1166	*
α_{ch}	1.5844	0.3800	***
α_{hdw5}	0.9834	0.7125	
α_{hdw10}	1.6783	0.3490	***
α_{hdw15}	2.2241	0.2204	***
α_{hdw20}	2.6955	0.1626	***
α_{hdw30}	3.1937	0.1468	***
α_{hdw60}	3.9037	0.1259	***
α_{hdw120}	4.7252	0.3287	***
α_{wt}	0.5951	0.1656	***
β_{hdw60m}	-25.0272	30.9801	
$\beta_{hdw120m}$	-92.3827	45.8842	**
σ	1.1283	0.1304	***
$\bar{u}$	-0.7379	0.1404	***
μ	8.0830	0.4725	***

Segment:	PT Single-mode Train		
Model:	Model with headway dummies		
Log. Likelihood:		-1612.5	
Number of Halton draws:		300	
Number of estimated parameters:		15	
Number of observations:		3337	
Number of individuals:		503	
Parameter	**Estimate**	**Std err**	
α_{ae}	0.0710	0.0849	
α_{ch}	2.4845	0.1856	***
α_{hdw5}	1.2292	1.5124	
α_{hdw10}	2.2382	0.4719	***
α_{hdw15}	2.9621	0.2435	***
α_{hdw20}	3.2582	0.1909	***
α_{hdw30}	3.2811	0.1899	***
α_{hdw60}	3.5265	0.1503	***
α_{hdw120}	4.1278	0.1019	***
α_{wt}	0.2062	0.2328	
β_{hdw60m}	-38.4061	14.3530	***
$\beta_{hdw120m}$	-59.6676	13.7479	***
σ	1.5002	0.1195	***
$\bar{u}$	-0.1947	0.1083	*
μ	7.9521	0.3929	***

Table 44: Models with piecewise linear headway

Segment:	PT Single-mode Bus		
Model:	Model with piecewise linear headway (split: 20 minutes).		
Log. Likelihood:		-3614.9	
Number of Halton draws:		300	
Number of estimated parameters:		10	
Number of observations:		7472	
Number of individuals:		1103	
Parameter	**Estimate**	**Std err**	
α_{ae}	0.5039	0.0748	***
α_{ch}	2.4148	0.1301	***
$\alpha_{hdwHIGH}$	-0.8391	0.0776	***
α_{hdwLOW}	0.0500	0.0978	
α_{wt}	0.5606	0.1129	***
β_{hdw60m}	-23.1751	29.8725	
$\beta_{hdw120m}$	-52.0266	32.4897	
σ	1.3013	0.0829	***
$\bar{u}$	-1.2334	0.0869	***
μ	6.7802	0.2100	***

Segment:	PT Single-mode S-train		
Model:	Model with piecewise linear headway (split: 10 minutes).		
Log. Likelihood:		-799.12	
Number of Halton draws:		300	
Number of estimated parameters:		10	
Number of observations:		1822	
Number of individuals:		264	
Parameter	**Estimate**	**Std err**	
α_{ae}	0.2106	0.1172	*
α_{ch}	1.6126	0.3758	***
$\alpha_{hdwHIGH}$	-0.0909	0.1242	
α_{hdwLOW}	-0.3571	0.3255	
α_{wt}	0.6069	0.1661	***
β_{hdw60m}	-26.5637	31.7667	
$\beta_{hdw120m}$	-85.6116	30.6834	***
σ	1.1319	0.1299	***
$\bar{u}$	-0.7495	0.1409	***
μ	8.1856	0.4805	***

Segment:	PT Single-mode Train		
Model:	Model with piecewise linear headway (split: 15 minutes).		
Log. Likelihood:		-1618.2	
Number of Halton draws:		300	
Number of estimated parameters:		10	
Number of observations:		3337	
Number of individuals:		503	
Parameter	**Estimate**	**Std err**	
α_{ae}	0.0743	0.0848	
α_{ch}	2.4500	0.1924	***
$\alpha_{hdwHIGH}$	-0.9878	0.0859	***
α_{hdwLOW}	0.5768	0.1983	***
α_{wt}	0.2381	0.2267	
β_{hdw60m}	-46.4768	14.8785	***
$\beta_{hdw120m}$	-62.0523	14.2403	***
σ	1.4952	0.1190	***
$\bar{u}$	-0.1909	0.1079	*
μ	8.1816	0.4085	***

Table 45: Models with reference-dependent preferences

Segment:	PT Single-mode Bus		
Model:	Model with reference-dependent preferences for all components but interchange waiting time and interchanges.		
Log. Likelihood:		-3578.6	
Number of Halton draws:		300	
Number of estimated parameters:		14	
Number of observations:		7472	
Number of individuals:		1103	
Parameter	**Estimate**	**Std err**	
α_{ae}	0.5726	0.1133	***
α_{ch}	2.5037	0.1508	***
$\alpha_{hdwHIGH}$	-0.8079	0.1112	***
α_{hdwLOW}	0.0842	0.1311	
α_{wt}	0.6742	0.1431	***
β_{hdw60m}	-7.5819	41.6282	
$\beta_{hdw120m}$	-36.8721	44.8964	
η_{ae}	0.2850	0.0672	***
η_{c}	0.1692	0.0438	***
η_{hdw}	0.2507	0.0609	***
η_{iv}	0.4771	0.1601	***
σ	1.3189	0.0846	***
$\bar{u}$	-1.3469	0.1199	***
μ	7.0337	0.2247	***

Segment:	PT Single-mode Metro		
Model:	Model with reference-dependent preferences for access/egress time.		
Log. Likelihood:		-364.16	
Number of Halton draws:		300	
Number of estimated parameters:		8	
Number of observations:		843	
Number of individuals:		126	
Parameter	**Estimate**	**Std err**	
α_{ae}	0.2761	0.2352	
α_{ch}	0.4408	1.5040	
α_{hdw}	0.2812	0.2451	
α_{wt}	0.8944	0.2581	***
η_{ae}	0.3291	0.1331	**
σ	1.2852	0.2317	***
$\bar{u}$	-0.8231	0.2765	***
μ	7.0617	0.6166	***

Segment:	PT Single-mode S-train		
Model:	Model with reference-dependent preferences for cost and access/egress time.		
Log. Likelihood:		-791.26	
Number of Halton draws:		300	
Number of estimated parameters:		12	
Number of observations:		1822	
Number of individuals:		264	
Parameter	**Estimate**	**Std err**	
α_{ae}	0.2273	0.1240	*
α_{ch}	1.6451	0.3823	***
$\alpha_{hdwHIGH}$	-0.0684	0.1291	
α_{hdwLOW}	-0.3568	0.3379	
α_{wt}	0.6217	0.1729	***
β_{hdw60m}	-22.2373	34.6001	
$\beta_{hdw120m}$	-82.7265	33.4128	**
η_{ae}	0.2300	0.0938	**
η_{c}	0.2268	0.0808	***
σ	1.1631	0.1351	***
$\bar{u}$	-0.7794	0.1462	***
μ	8.3986	0.4912	***

Segment:	PT Single-mode Train		
Model:	Model with reference-dependent preferences for all components but interchange waiting time and interchanges.		
Log. Likelihood:		-1599.5	
Number of Halton draws:		300	
Number of estimated parameters:		14	
Number of observations:		3337	
Number of individuals:		503	
Parameter	**Estimate**	**Std err**	
α_{ae}	0.0516	0.1059	
α_{ch}	2.4383	0.2025	***
$\alpha_{hdwHIGH}$	-1.0639	0.1128	***
α_{hdwLOW}	0.3746	0.2738	
α_{wt}	0.2625	0.2343	
β_{hdw60m}	-42.1865	15.6613	***
$\beta_{hdw120m}$	-55.3124	15.2917	***
η_{ae}	0.2935	0.1091	***
η_{c}	0.2055	0.0610	***
η_{hdw}	0.2875	0.1112	***
η_{iv}	0.3293	0.1312	**
σ	1.4947	0.1205	***
$\overline{u}$	-0.2417	0.1175	**
μ	8.2714	0.4330	***

Table 46: Model with generalised VTT distribution

Segment:	PT Single-mode Bus		
Model:	Model with generalised distribution of u, and reference-dependent preferences for all components but interchange waiting time and interchanges.		
Log. Likelihood:		-3571.8	
Number of Halton draws:		300	
Number of estimated parameters:		17	
Number of observations:		7472	
Number of individuals:		1103	
Parameter	**Estimate**	**Std err**	
α_{ae}	0.5705	0.1125	***
α_{ch}	2.4988	0.1500	***
$\alpha_{hdwHIGH}$	-0.8139	0.1106	***
α_{hdwLOW}	0.0890	0.1299	
α_{wt}	0.6699	0.1424	***
β_{hdw60m}	-3.7779	39.9268	
$\beta_{hdw120m}$	-32.3044	42.8409	
η_{ae}	0.2806	0.0668	***
η_{c}	0.1687	0.0437	***
η_{hdw}	0.2487	0.0602	***
η_{iv}	0.4763	0.1588	***
σ	2.1940	0.2717	***
$\overline{u}$	0.5550	0.2576	**
μ	7.0937	0.2260	***
δ_1 *)	-0.8638	0.3756	**
δ_2 *)	0.3071	0.2166	
δ_3 *)	0.5145	0.2067	**

*) Transformation parameters, see Fosgerau and Bierlaire (2005).
Lognormal VTT corresponds to $\delta_1 = \delta_2 = \delta_3 = 0$.

Table 47: Models with distance-specific parameters

Segment:	PT Single-mode Bus		
Model:	Model with distance-specific parameters.		
Log. Likelihood:		-3575.4	
Number of Halton draws:		300	
Number of estimated parameters:		21	
Number of observations:		7472	
Number of individuals:		1103	
Parameter	**Estimate**	**Std err**	
α_{ae}^{L}	0.5149	0.1320	***
α_{ae}^{S}	0.6142	0.1385	***
α_{ch}^{L}	2.7065	0.2076	***
α_{ch}^{S}	2.4228	0.1924	***
$\alpha_{hdwHIGH}^{L}$	-0.8464	0.1280	***
$\alpha_{hdwHIGH}^{S}$	-0.7730	0.1383	***
α_{hdwLOW}^{L}	0.0639	0.2311	
α_{hdwLOW}^{S}	0.0848	0.1508	
α_{wt}^{L}	0.5480	0.2426	**
α_{wt}^{S}	0.7241	0.1638	***
β_{hdw60m}	-1.2044	39.5469	
$\beta_{hdw120m}$	-30.0121	42.3908	
η_{ae}	0.2869	0.0674	***
η_{c}	0.1672	0.0439	***
η_{hdw}	0.2533	0.0625	***
η_{iv}	0.4787	0.1613	***
σ^{L}	1.4638	0.1350	***
σ^{S}	1.2104	0.1063	***
$\bar{u}^{L}$	-1.4033	0.1487	***
$\bar{u}^{S}$	-1.3238	0.1492	***
μ	7.0207	0.2295	***

Segment:	PT Single-mode S-train		
Model:	Model with distance-specific parameters.		
Log. Likelihood:		-785.68	
Number of Halton draws:		300	
Number of estimated parameters:		19	
Number of observations:		1822	
Number of individuals:		264	
Parameter	**Estimate**	**Std err**	
α_{ae}^{L}	0.0569	0.1503	
α_{ae}^{S}	0.4457	0.1861	**
α_{ch}^{L}	2.0644	0.3569	***
α_{ch}^{S}	1.1338	0.9475	
$\alpha_{hdwHIGH}^{L}$	-0.1693	0.1527	
$\alpha_{hdwHIGH}^{S}$	0.0713	0.1822	
α_{hdwLOW}^{L}	-0.2488	0.4456	
α_{hdwLOW}^{S}	-0.2244	0.4527	
α_{wt}^{L}	0.3474	0.2807	
α_{wt}^{S}	0.9157	0.2300	***
β_{hdw60m}	-16.6441	49.0624	
$\beta_{hdw120m}$	-84.4042	47.3109	*
η_{ae}	0.2174	0.0943	**
η_{c}	0.2189	0.0799	***
σ^{L}	1.1731	0.1975	***
σ^{S}	1.0179	0.1756	***
$\bar{u}^{L}$	-0.4814	0.1832	***
$\bar{u}^{S}$	-1.1732	0.2137	***
μ	8.5564	0.4979	***

Segment:	PT Single-mode Train		
Model:	Model with distance-specific parameters.		
Log. Likelihood:		-1574.2	
Number of Halton draws:		300	
Number of estimated parameters:		21	
Number of observations:		3337	
Number of individuals:		503	
Parameter	**Estimate**	**Std err**	
α_{ae}^{L}	-0.1024	0.1371	
α_{ae}^{S}	0.3043	0.1557	*
α_{ch}^{L}	3.0467	0.2266	***
α_{ch}^{S}	2.3217	0.3145	***
$\alpha_{hdwHIGH}^{L}$	-0.9591	0.1311	***
$\alpha_{hdwHIGH}^{S}$	-0.9327	0.1577	***
α_{hdwLOW}^{L}	-0.7975	1.6581	
α_{hdwLOW}^{S}	0.5930	0.2962	**
α_{wt}^{L}	-2.8856	10.5743	
α_{wt}^{S}	0.6979	0.2429	***
β_{hdw60m}	-45.8138	21.0095	**
$\beta_{hdw120m}$	-59.4791	20.6867	***
η_{ae}	0.3155	0.1101	***
η_{c}	0.1734	0.0589	***
η_{hdw}	0.2986	0.1129	***
η_{iv}	0.3059	0.1251	**
σ^{L}	1.2413	0.1432	***
σ^{S}	1.2443	0.1595	***
$\bar{u}^{L}$	0.2576	0.1284	**
$\bar{u}^{S}$	-0.9555	0.1767	***
μ	8.2148	0.4481	***

Table 48: Model with distance-specific in-vehicle and access/egress time

Segment:	PT Single-mode Train		
Model:	Model with distance-specific parameters for in-vehicle time and access/egress time.		
Log. Likelihood:		-1579.1	
Number of Halton draws:		300	
Number of estimated parameters:		17	
Number of observations:		3337	
Number of individuals:		503	
Parameter	**Estimate**	**Std err**	
α_{ae}^{L}	-0.1273	0.1423	
α_{ae}^{S}	0.2577	0.1216	**
α_{ch}	2.5591	0.2020	***
α_{hdwLOW}	0.4664	0.2875	
$\alpha_{hdwHIGH}$	-0.9594	0.1118	***
α_{wt}	0.3394	0.2402	
β_{hdw60m}	-43.9579	19.2460	**
$\beta_{hdw120m}$	-59.0496	19.4737	***
η_{ae}	0.3088	0.1104	***
η_{c}	0.1722	0.0588	***
η_{hdw}	0.2906	0.1121	***
η_{iv}	0.3166	0.1288	**
σ^{L}	1.2661	0.1474	***
σ^{S}	1.2411	0.1563	***
$\bar{u}^{L}$	0.2550	0.1307	*
$\bar{u}^{S}$	-0.9064	0.1449	***
μ	8.3948	0.4432	***

7.6 Estimation results – PT multiple-mode

Table 49: Base model

Segment:	PT Mult-mode Bus-Metro		
Model:	Base model		
Log. Likelihood:	-331.28		
Number of Halton draws:	300		
Number of estimated parameters:	14		
Number of observations:	797		
Number of individuals:	104		
Parameter	**Estimate**	**Std err**	
α_{ae}^{A}	0.6287	0.4664	
α_{ae}^{BC}	-0.4737	0.4458	
α_{ch}	2.1505	0.3830	***
α_{hdw}^{A}	0.0751	0.5115	
α_{hdw}^{BC}	-0.7146	0.4431	
$\alpha_{ivMetro}^{A}$	-0.6525	1.2961	
$\alpha_{ivMetro}^{BC}$	-0.0172	0.1705	
α_{wt}^{A}	0.6485	0.5087	
α_{wt}^{BC}	-0.5632	0.8719	
σ	1.0394	0.2087	***
$\bar{u}^{A}$	-1.7085	0.4911	***
$\bar{u}^{BC}$	-0.8737	0.2170	***
μ^{A}	8.3430	1.2455	***
μ^{BC}	7.8502	1.0328	***

Segment:	PT Mult-mode Metro-Train		
Model:	Base model		
Log. Likelihood:	-511.31		
Number of Halton draws:	300		
Number of estimated parameters:	14		
Number of observations:	1137		
Number of individuals:	149		
Parameter	**Estimate**	**Std err**	
α_{ae}^{A}	0.2712	0.5570	
α_{ae}^{BC}	0.1902	0.3764	
α_{ch}	2.5133	0.4875	***
α_{hdw}^{A}	0.1808	0.5693	
α_{hdw}^{BC}	0.5518	0.3271	*
$\alpha_{ivTrain}^{A}$	0.2942	0.5748	
$\alpha_{ivTrain}^{BC}$	-0.2094	0.1526	
α_{wt}^{A}	0.5618	0.5501	
α_{wt}^{BC}	0.6606	0.5102	
σ	1.3338	0.2406	***
$\bar{u}^{A}$	-0.9229	0.5775	
$\bar{u}^{BC}$	-1.1900	0.3203	***
μ^{A}	10.1270	1.5305	***
μ^{BC}	6.3330	0.7577	***

Segment:	PT Mult-mode Bus-Train		
Model:	Base model		
Log. Likelihood:		-1808	
Number of Halton draws:		300	
Number of estimated parameters:		14	
Number of observations:		4100	
Number of individuals:		537	
Parameter	**Estimate**	**Std err**	
α_{ae}^{A}	0.7231	0.3223	**
α_{ae}^{BC}	-0.3377	0.2257	
α_{ch}	1.4715	0.6315	**
α_{hdw}^{A}	-0.0634	0.3249	
α_{hdw}^{BC}	-0.7042	0.1609	***
$\alpha_{ivTrain}^{A}$	0.5481	0.3243	*
$\alpha_{ivTrain}^{BC}$	-0.2342	0.0740	***
α_{wt}^{A}	0.9955	0.3187	***
α_{wt}^{BC}	0.4139	0.2975	
σ	1.5161	0.1139	***
$\bar{u}^{A}$	-1.3517	0.3340	***
$\bar{u}^{BC}$	-0.5186	0.1147	***
μ^{A}	8.8539	0.5349	***
μ^{BC}	6.3497	0.3747	***

Table 50: Model with common parameters

Segment:	PT Mult-mode Bus-Metro		
Model:	Common parameters		
Log. Likelihood:		-335.64	
Number of Halton draws:		300	
Number of estimated parameters:		8	
Number of observations:		797	
Number of individuals:		104	
Parameter	**Estimate**	**Std err**	
α_{ae}	0.0719	0.1976	
α_{ch}	2.1447	0.2408	***
α_{hdw}	-0.4548	0.2503	*
$\alpha_{ivMetro}$	-0.2407	0.2216	
α_{wt}	0.0723	0.2520	
σ	1.0501	0.2120	***
u	-1.1181	0.1950	***
μ	8.4531	0.7634	***

Segment:	PT Mult-mode Metro-Train		
Model:	Common parameters		
Log. Likelihood:		-516.55	
Number of Halton draws:		300	
Number of estimated parameters:		8	
Number of observations:		1137	
Number of individuals:		149	
Parameter	**Estimate**	**Std err**	
α_{ae}	0.1607	0.1856	
α_{ch}	2.1572	0.2459	***
α_{hdw}	0.1906	0.1852	
$\alpha_{ivTrain}$	-0.1244	0.0953	
α_{wt}	0.5107	0.2103	**
σ	1.1554	0.2195	***
u	-0.8604	0.1955	***
μ	7.7959	0.5654	***

Table 51: Model with common parameters, except scale.

Segment:	PT Mult-mode Bus-Train		
Model:	Common parameters, except scale		
Log. Likelihood:		-1814.9	
Number of Halton draws:		300	
Number of estimated parameters:		9	
Number of observations:		4100	
Number of individuals:		537	
Parameter	**Estimate**	**Std err**	
α_{ae}	-0.0555	0.0932	
α_{ch}	1.7111	0.2612	***
α_{hdw}	-0.7638	0.0948	***
$\alpha_{ivTrain}$	-0.2372	0.0593	***
α_{wt}	0.3265	0.1105	***
σ	1.5298	0.1128	***
u	-0.5907	0.0937	***
μ^{A}	9.3613	0.5242	***
μ^{BC}	6.3032	0.3610	***

7.7 Wald tests

Table 52: Wald tests of combining alphas for short and long distances.

Segment	Hypothesis	Est. diff. $(\alpha_i^L - \alpha_i^S)$	Std. dev. of est. diff.	test statistic[18]	p-value
Train	$H_0 : \alpha_{ae}^L = \alpha_{ae}^S$	-0.4068	0.1855	-2.193	3%
	$H_0 : \alpha_{ch}^L = \alpha_{ch}^S$	0.7249	0.3855	1.881	6%
	$H_0 : \alpha_{hdwHIGH}^L = \alpha_{hdwHIGH}^S$	-0.0264	0.1712	-0.154	88%
	$H_0 : \alpha_{hdwLOW}^L = \alpha_{hdwLOW}^S$	-1.3905	1.6192	-0.859	39%
	$H_0 : \alpha_{wt}^L = \alpha_{wt}^S$	-3.5835	10.5742	-0.339	73%

Table 53: Wald tests of combining alphas for part A and parts B,C.

Segment	Hypothesis	Est. diff.	Std. dev. of est. diff.	test statistic[19]	p-value
Bus-Metro	$H_0 : \alpha_{ae}^A = \alpha_{ae}^{BC}$	1.1024	0.6427	1.715	9%
	$H_0 : \alpha_{hdw}^A = \alpha_{hdw}^{BC}$	0.7898	0.6853	1.152	25%
	$H_0 : \alpha_{ivMetro}^A = \alpha_{ivMetro}^{BC}$	-0.6353	1.3068	-0.486	63%
	$H_0 : \alpha_{wt}^A = \alpha_{wt}^{BC}$	1.2117	0.9999	1.212	23%
	$H_0 : \bar{u}^A = \bar{u}^{BC}$	-0.8348	0.5142	-1.624	10%
	$H_0 : \mu^A = \mu^{BC}$	0.4928	1.6414	0.300	76%
Bus-Train	$H_0 : \alpha_{ae}^A = \alpha_{ae}^{BC}$	1.0608	0.3946	2.688	1%
	$H_0 : \alpha_{hdw}^A = \alpha_{hdw}^{BC}$	0.6408	0.3626	1.767	8%
	$H_0 : \alpha_{ivTrain}^A = \alpha_{ivTrain}^{BC}$	0.7822	0.3321	2.356	2%
	$H_0 : \alpha_{wt}^A = \alpha_{wt}^{BC}$	0.5816	0.4369	1.331	18%
	$H_0 : \bar{u}^A = \bar{u}^{BC}$	-0.8331	0.3425	-2.433	1%
	$H_0 : \mu^A = \mu^{BC}$	2.5042	0.6586	3.802	0%
Metro-Train	$H_0 : \alpha_{ae}^A = \alpha_{ae}^{BC}$	0.0810	0.7015	0.115	91%
	$H_0 : \alpha_{hdw}^A = \alpha_{hdw}^{BC}$	-0.3710	0.6892	-0.538	59%
	$H_0 : \alpha_{ivTrain}^A = \alpha_{ivTrain}^{BC}$	0.5036	0.5904	0.853	39%
	$H_0 : \alpha_{wt}^A = \alpha_{wt}^{BC}$	-0.0988	0.7200	-0.137	89%
	$H_0 : \bar{u}^A = \bar{u}^{BC}$	0.2671	0.6661	0.401	69%
	$H_0 : \mu^A = \mu^{BC}$	3.7940	1.8164	2.089	4%

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[18] The test statistic equals the estimated difference $(\alpha_i^L - \alpha_i^S)$ divided by its estimated standard deviation. Under H_0, it is asymptotically $N(0,1)$ -distributed.

[19] The test statistic equals the estimated difference $(\alpha_i^L - \alpha_i^S)$ divided by its estimated standard deviation. Under H_0, it is asymptotically $N(0,1)$ -distributed.